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AKUNTANSI & PERPAJAKAN

Predicting Financial Distress In Indonesia, Malaysia, And Thailand Transportation & Tourism Companies: A Comparative Analysis Of Altman, Springate, Ohlson, Zmijewski, And Grover Models

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ABSTRACT

This study delves into the world of predictive models, aiming to anticipate financial distress in the tourism and transportation sectors across Indonesia, Thailand, and Malaysia. The research scrutinizes five distinguished models – Altman, Springate, Ohlson, Zmijewski, and Grover – to illuminate the evolving financial distress patterns. The research starts by precisely evaluating these financial models' forecasting capabilities, leveraging an extensive dataset from 2018 to 2022. This thorough assessment gauges the accuracy inherent in each model, unveiling their performance within the unique economic landscapes of these three nations.

The research identifies models that consistently hit the mark in accuracy through the prism of cross-country and multi-year evaluations. The findings underscore the predictive prowess of each model in foreseeing financial distress across the selected companies. However, these models exhibit distinct accuracy rates in the grand scheme and when zooming into individual countries. The Grover Model is the champion across the chosen countries, boasting the highest accuracy scores. In country-specific analyses, Zmijewski's predictive prowess shines as the most reliable for Malaysia and Thailand. Meanwhile, Grover steals the spotlight in Indonesia by outperforming its counterparts in predictive accuracy.

Keyword: Altman, Grover, Springate, Ohlson, Zmijewski,

INTRODUCTION

Financial Distress, frequently referred to as a "financial crisis," occurs when there is insufficient cash flow to pay off current debt. When a publicly traded business has a financial crisis or bankruptcy, it may have far-reaching effects on the stability of the capital market and possibly cause investor suffering and economic losses. Assume that public companies have access to a financial crisis early warning model. In such a situation, business managers can take precautions sooner to prevent the spread of destruction. The financial crisis warning model additionally has the potential to strengthen the capital market by reassuring investors who may be oblivious to the

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company's operational status. Hence, the appropriate warning model can detect problems with publicly traded companies to prevent investors from incurring substantial losses (Cheng et al., 2018)

Significant disruptions to the worldwide economy have been created by the COVID-19 pandemic. By the end of the first quarter of 2020, the COVID-19 pandemic stopped international travel immediately by restricting on international travel and increased border controls fueling international trade costs and having a significant impact on the tourism industry. Numerous developed and developing nations rely extensively on tourism for employment, government revenue, and foreign exchange earnings Alam & Parveen, (2021). Certain businesses, such as tourism, aviation, the restaurant industry, and transportation, are more likely to experience financial difficulties as a result of variations in the economy, changes in legislation, and other external factors.

Based on the data from UNWTO, in 2020, the tourism sector experienced a drastic decline to -72.1%. Quoted from UNWTO, (2022), tourism arrivals have increased quite significantly, more than doubling those in 2021 while remaining 37% lower than in 2019. According to (UNWTO, 2020), the majority of South-East Asia destinations experienced growth in 2019, with Thailand, the subregion's largest destination, which added almost 3 million more arrivals and USD 6 billion more in receipts, which was ranked fourth among the top 10 tourism earners by receipts and ninth among the top 10 tourism earners by arrivals. Then, followed by Malaysia; and Indonesia, the tourism arrivals of 26,18 and 15 US dollars, respectively. According to Fitzpatrick's statements in Tuvadaratragool, (2013), this is undesirable for stakeholders such as workers, bank creditors, shareholders, communities, and governments because these groups suffer money on their investments whenever an entity is lost for any reason.

The inclusion of Thailand and Malaysia as focal countries in this research study is justified by several compelling academic reasons. Firstly, Thailand's selection is substantiated by its prominent stature within the global tourism industry. According to Uwanto's insights from 2019, Thailand consistently ranks among the top 10 tourist destinations worldwide. This fact highlights the nation's significant economic reliance on tourism and its susceptibility to financial distress in the event of external shocks or crises. The decision to include Thailand as a research subject is academically sound as it provides a unique opportunity to investigate the financial stability and resilience of an economy heavily dependent on tourism-driven revenues.

The Altman Z Score, Springate, Zmijewski, Grover, and Ohlson models are only a few of the many analytical frameworks used by academics to assess businesses' financial difficulties. Some researchers claim that the Zmijewski model provides the most reliable results for predicting financial distress. According to Fatmawati, (2012), the Zmijewski model is a ratio analysis used to evaluate a company's performance, leverage, and liquidity. Using a determination coefficient test, Susilawati, (2017), research indicates that the Zmijewski Model has the highest level of accuracy in predicting financial distress. The results of this study are directly comparable to those of Fatmawati, (2012) and Aderibigbe, (2018), which demonstrate the fact that the Zmijewski model is the most accurate predictor of financial distress with the highest percentage level compared to analysis of the other models. In addition, research by Kustianto et al., (2016) concluded that the Zmijewski model is the most appropriate model for predicting future financial distress in a company. Other researchers claim that the Grover model provides the most reliable results for predicting financial distress (Prihanthini & Sari, 2013) Pertiwi, 2020) (Sudrajat & Wijayanti, 2019). (Savitri, 2014) (Primasari, 2018) indicates that the Altman Model has the highest level of accuracy in predicting financial distress. (Priambodo, 2017) (Azizah, 2017) conclude that Springate is the most appropriate model for predicting future financial distress.

With the assistance of this research, an accurate model for forecasting financial distress will be constructed, which can then be utilized to assist businesses in overcoming challenges related to financial distress. This research will contribute to the advancement of financial science and risk management, as well as provide businesses with solutions for managing financial risks and reducing the probability of future financial distress.The researcher developed the following research objectives based on the formulation of the problem above: Analyzing the financial distress model which is most accurate. As a result, management may get a more accurate picture of any impending financial difficulties and move swiftly to address them. The author aims to perform research titled "**Predicting Financial Distress In Indonesia, Malaysia, and Thailand Transportation & Tourism Companies: A Comparative Analysis of Altman, Springate, Ohlson, Zmijewski, and Grover Models**"

Financial distress refers to a scenario where a company encounters difficulties in fulfilling its financial obligations. This can result in various actions such as debt restructuring, bankruptcy, or failure to meet contractual obligations Altman, (1984). Financial distress can be caused by various factors, including the company's capital structure and broader macroeconomic conditions. This statement aligns with Merton's in Merton, (1974), which suggests that the capital structure of a company can impact its risk of financial distress. Through his research, he has demonstrated that a greater reliance on debt in a company's capital structure can elevate the likelihood of bankruptcy. Furthermore, according to Opler & Titman, (1994), companies that have high levels of leverage are at a greater risk of experiencing financial distress. The performance of a company plays a crucial role in assessing the likelihood of financial distress. Ohlson, (1980) found that companies with poor financial ratios, such as low liquidity and negative profitability, are more likely to go bankrupt. According to research conducted by Sutra & Mais, (2019), Financial Distress in a company can be influenced by the company's internal factors, namely profitability, liquidity, leverage, operating capacity and sales growth. Discover the true meaning of financial distress: a scenario where a corporation is unable to fulfil its financial commitments due to insufficient cash flow, as revealed by research conducted in Fachrudin, (2020).

In addition to internal factors, macroeconomic conditions can also positively impact the likelihood of financial stability. Hackbarth et al., (2006) discovered that by taking into account factors such as capital structure, credit risk, and macroeconomic conditions, we can better understand and manage the risk of financial distress. External factors such as unemployment rates, interest rates, economic growth, government spending, exchange rates, and aggregate savings can affect a company's ability to meet its financial obligations and avoid financial distress Shumway et al., (2001). Having financial flexibility is a great way to minimize the chances of facing financial difficulties. Amidst the volatile waves of economic unpredictability, Gamba & Triantis, (2008) reveal an indication of hope for companies with greater financial flexibility. According to their research, companies of this nature exhibit a distinct ability to withstand financial difficulties and successfully navigate through them. In addition to this, the availability of financial resources is another factor that can affect the probability of experiencing financial trouble. Discoveries from Whited, (2006) reveal that companies facing significant financial constraints are more susceptible to financial distress.

From Damodaran's research (1997), which is briefly outlined in Curry et al., (2018), it has been observed that financial difficulties in companies are often linked to micro factors, i.e. internal conditions of the company. There are certain internal factors that may have an impact on financial stability, which are: 1) **Negative Cash Flow:**The alarming presence of negative cash flow stands as the beginning of financial chaos, signaling a dearth of liquid assets and an unstable state of financial issues affairs. Insufficient income can lead to financial difficulties for a company, making it challenging to meet its operating expenses and other financial obligations (Damodaran, 1997). 2) **High Leverage:** Companies that carry significant debt are vulnerable to financial distress, particularly if they lack the necessary resources to repay their debts (Damodaran, 1997). 3) **Challenges with Operational Performance:** When operating expenses exceed income, it may indicate potential financial difficulties. The company experienced a challenging financial situation due to a negative cash flow. Companies that are unable to adapt to changes in the industry are at risk of losing market share, experiencing decreased revenues, and facing financial difficulties (Opler & Titman, 1994).

Fast forwarding yet again, to the year 2002, Platt & Platt, (2014) demonstrated the immense usefulness of these financial distress prediction models. These models provide an early warning system for potential financial trouble and shed light on the factors that contribute to such distress. This enables business leaders to take proactive measures to mitigate these risks

Back in the revolutionary year of 1968, the ingenious mind of Edward I. Altman gave birth to a remarkable bankruptcy prediction model called the Altman Z-score Altman, (1984). The Altman Z-score model has emerged as a trusted ally, eagerly embraced by investors, financial analysts, and creditors alike. It stands as a steadfast pillar of assessment, enabling a deep dive into a company's financial health and offering a glimpse into the crystal-clear waters of bankruptcy probability Beaver, (1966).

Research cited in Tania et al., (2021) reveals that the Altman Z-Score has evolved through three significant changes. The initial Altman Z-Score model (1968) was designed exclusively for publicly traded manufacturing companies. This was followed by the Revised Altman Z-Score (1983), an enhancement of the previous formula, which extended its use to both public and private manufacturing companies. The final version, the Modified Altman Z-Score (1995), broadened the model's applicability to encompass a variety of industries, whether public or private.

The Springate Model, introduced by Springate in 1978, is a methodology for forecasting financial distress based on a company's financial ratios. This model, like Altman's, uses Multiple Discriminant Analysis (MDA) as its basis. As outlined in the research referenced in Erdes, (2021), Springate identified four ratios believed to distinctly differentiate between companies in distress and those not in distress, following a testing procedure similar to Altman's (1968) approach.

The Ohlson Model, developed by James A. Ohlson in 1980, is a method utilized for predicting corporate bankruptcy Ohlson, (1980). This model materialized following the introduction of the Z-score method by Altman in 1968. Altman's model is a multivariate analysis tool aimed at forecasting corporate bankruptcy with a considerable degree of reliability and precision (Altman, 1984).Also known as the O-Score Model, the Ohlson model employs logistic regression analysis to estimate a company's bankruptcy probability. This model takes into account several financial variables deemed significant in evaluating company performance and the associated risk of bankruptcy.

The Zmijewski model, formulated by Edward Zmijewski in 1984, has gained recognition as an effective instrument for detecting financial vulnerabilities in firms across various industries. Zmijewski designed this model with the intent of delivering a precise and efficient means of evaluating firms at risk of encountering financial distress Zmijewski, (1984). This model employs several financial ratios as independent variables in a probit analysis, which are then applied to estimate the likelihood of financial distress within a firm. As described in the study Erdes, (2021), this model's estimation was based on a sample comprised of 75 bankrupt companies and 73 financially stable and robust companies from the period between 1972 and 1978. In this research, Zmijewski utilized the F-Test to get closer financial ratios between stable and unstable company groups, including factors such as return on investment, liquidity, leverage, turnover, fixed payment coverage, trends, firm size, and stock return volatility. The findings indicated a significant divergence between financially stable and unstable companies.

In the historical record of financial prognostication, the Grover model stands as a towering achievement. Conceived by the brilliant mind of Grover in the year of 1996, this method for predicting financial distress has since become an integral component of the field. The ultimate objective is to facilitate the process of decision-making by determining enterprises that are at risk of coming across financial collapse in the forthcoming times. The model has garnered immense popularity within the financial literary globe and has undergone numerous modifications to enhance its predictive prowess. The intelligent research conducted by Prihanthini & Sari, (2013) clarifies on the Grover model, a masterful creation that was ingeniously crafted through the improvement and re-evaluation of the Altman Z-Score model. In order to scrutinize the precision of the Grover model, an investigation was carried out employing the identical sample utilized in the Altman Z-Score model back in 1968. The sample consisted of 70 companies consisting of 35 companies that experienced bankruptcy and 35 companies that did not experience bankruptcy in the period 1982 to 1996.

After applying the five prediction models to the data of companies in the studied sectors, a writer examined the variations in the scores and accuracy levels offered by each model. Author assessed the effectiveness of these models in predicting financial distress by utilizing suitable evaluation metrics, such as accuracy. Through this research, it was observed that each prediction model possesses distinct advantages and limitations.

METHOD, DATA, AND ANALYSIS

This study was conducted with the aim of empirically comparing the accuracy of the five main prediction models in predicting financial distress in a company. These models include the Altman model, the Springate model, the Ohlson O-Score model, the Zmijewski model, and the Grover model.

Financial Distress Prediction Models

Model Altman Z-Score Analysis

This is the formula used for the Modified Altman Z-Score:

Z-Score = 6,56 Working Capital/Total Assets +3,26 Retained Earnings/Total Assets +6,72 Profit Before Interest and Tax/Total Assets +1,05 Book Value of Equity/Total Debt

Altman uses cut off values of 2.675 and 1.81. This means that if the Z value obtained is more than 2.675, the company is predicted not to experience financial distress in the future. A company whose Z value is between 1.81 and 2.675 means that the company is in a gray area, and if the score Z < 1.81 then the company is classified as experiencing financial problems.

Model Springate Analysis

The S-Score value in this model is determined using the subsequent formula:

S-Score = 1.03 Working Capital / Total Assets + 0.33 Retained Earnings / Total Assets + 0.99 EBIT / Total Assets + 0.46 Equity / Total Liabilities

If the score obtained is S > 0.862 then the company is classified as healthy and if the score S < 0.862 then the company is classified as experiencing financial distress.

Model Ohlson Analysis

Here is the Ohlson Model formula:

$$\text{O-Score} = -1.32 - 0.407\,Y_1 + 6.03\,Y_2 - 1.43\,Y_3 + 0.0757\,Y_4 - 1.72\,Y_5 + 0.285\,Y_6 - 0.521\,Y_7 + 0.593\,Y_8 + 0.844\,Y_9$$

The following provides an explanation of the variables Y1 through Y9 in the O-Score formula:

Y1 = log (total assets/Gross National Product price index) of company i in year t.
Y2 = Total liabilities divided by total assets of company i in year t.
Y3 = working capital divided by total assets of company i in year t.
Y4 = current liabilities divided by current assets of company i in year t.
Y5 = a dummy variable, 1 if total liabilities exceed total assets for company i in year t, otherwise 0.
Y6 = net income divided by total assets of company i in year t.
Y7 = operating cash flow divided by total liabilities of company i in year t.
Y8 = a dummy variable, 1 if net income is negative for the last two (2) years, otherwise 0.
Y9 = (net income in year t - net income in year t-1) / absolute value of net income in year t plus absolute value of net income in year t-1.

The Ohlson Model employs a cut-off value of 0.038, or 3.8%. This signifies that if a company attains a score exceeding 3.8%, it's anticipated that the company will face financial distress in the future. On the other hand, if the score is less than 3.8%, the company is predicted to avoid financial distress, according to Ohlson's research.

Model Zmijewski Analysis

The Zmijewski formula can be expressed as follows:
Z = -4.3 - 4.5 Return on Assets + 5.7 Debt Ratio - 0.004 Current Ratio

According to Zmijewski (1984), a company is perceived to be in financial distress if the Z value is equal to or greater than zero. Therefore, a company with a Z value equal to or exceeding zero is predicted to face financial distress in the future. On the other hand, companies with a Z value less than zero are predicted to avoid financial distress.

Model Grover Analysis

Jeffrey S. Grover (2001) produce the following functions in 2021:

Score = 1.650 Working capital/Total assets + 3.404 Earnings before interest and taxes/Total assets – 0.016 net income/total assets + 0.057

A score of less than or equal to -0.02 (Z -0.02) is required for the Grover model to classify a company as bankrupt (i.e., a Z -0.02). While the value for businesses classified as not insolvent is more than or equal to 0.01 (Z 0.01).

Financial Distress Calculation in Reality

Assessing whether a company is facing financial distress involves considering several key parameters. Researchers have identified three critical factors that play a role in identifying financial distress. These factors include:

Negative Cash Flow

This refers to a situation where a company's cash outflows exceed its cash inflows. It indicates that the company is spending more money than it's generating, which can lead to financial difficulties.

Annual Profit Deficit

This occurs when a company's annual profits, or net income, are in a deficit. In other words, the company is not generating enough revenue to cover its expenses and costs, which can impact its overall financial health.

Current Ratio Below One

The current ratio is a measure of a company's short-term liquidity and ability to cover its short-term liabilities with its short-term assets. A current ratio below one suggests that the company might struggle to meet its short-term obligations.

In the context of these criteria, researchers categorize a company as undergoing financial distress if it meets at least two out of the three established factors. On the other hand, if only one of these criteria is met, the company is considered to have a stable financial position.

This approach aims to improve the accuracy of assessing financial distress by considering a range of factors, rather than solely relying on the presence of negative income. This is because a company with negative income might not necessarily be in financial distress – there could be other factors at play.

Calculation of Accuracy Level

When the calculation of financial distress has been carried out using each analysis model, the next step is to calculate the accuracy level of each model used to get how much accuracy each analysis model has. Based on the narrative of Altman (1986), the level of accuracy is calculated using the formula:

$$\text{The accuracy level} = \frac{Total\ of\ Correct\ Prediction}{Total\ of\ Sampling}\ x\ 100\%$$

The "Total of Correct Prediction" refers to cases where the calculation results from a model match the prediction made using the three criteria mentioned above. On the other hand, the "Total of Mistaken Prediction" refers to the opposite, or the Total Sample minus the Total of Correct Prediction.

The calculation of the error rate is as follows:

$$\text{Type Error}\ \frac{Total\ of\ Mistaken\ Prediction}{Total\ of\ Sampling}\ x\ 100\%$$

POPULATION AND SAMPLING TECHNIQUE

The population of this research consists of transportation & tourism sector companies listed on the stock exchanges in Indonesia, Malaysia and Thailand. Purposive sampling was utilized as the sampling technique because it allowed for the collection of a representative sample based on previously established criteria and considerations. The following are the sample criteria:

a. Transportation & Tourism related businesses, including restaurant and hotel, that were listed on the stock exchanges of Indonesia, Malaysia, and Thailand at a certain time.
b. Businesses that throughout the specified time period submitted comprehensive financial reports (annual reports).
c. Companies whose financial reporting deadline is December 31

In the context of Indonesia, there are a total of 34 selected companies, while for Thailand, there are 14 companies, and for Malaysia, there are 17 companies. The purposive sampling technique makes it possible to choose businesses that match the precise specifications and qualities required for the investigation. This method guarantees that the sample is pertinent to the research's goals and offers valuable information about the health and financial performance of the hotel industry in the chosen nations.

DATA TYPES AND SOURCES

The type of data used in this research is a quantitative data. The source of data applied in this research is a secondary data. The source of data in this study is the company's financial statements obtained from the official website, namely:

https://www.idx.co.id/,
https://www.bursamalaysia.com/,
https://www.set.or.th/en/home.

DATA COLLECTION TECHNIQUE

Documentation is the method of data collecting in this study. The research approach employed in this study was looking at official papers such financial statements of companies listed on the Indonesia Stock Exchange, Malaysian Stock Exchange, and Thai Stock Exchange, as well as an overview of the company and its evolution. Additionally, library research was conducted as part of this study to gather data by reviewing the literature, gathering literature volumes, and compiling references pertinent to the field of study.

RESULTS AND DISCUSSION

The assessment of accuracy rates and error types plays a crucial role in evaluating the effectiveness of various analysis models. This evaluation process involves comparing the number of correct predictions to the total number of samples to calculate the accuracy rate. Likewise, determining error types entails comparing the number of incorrect predictions to the total number of samples.

By focusing on these metrics, people can ascertain the precision and reliability of each analysis model utilized. A higher percentage of accuracy signifies a lower error rate and, consequently, enhances the confidence and trustworthiness in the model's performance. Below, author present each model's computed accuracy rate and error type, revealing valuable insights into their respective predictive capabilities.

For this study, the accuracy rate and error type will be carefully assessed for each research subject hailing from three distinct countries, namely Indonesia, Malaysia, and Thailand. This evaluation will be performed independently for every country, allowing us to gain comprehensive insights into the predictive performance of the analysis models for each specific geographical context.

By adopting this approach, an author ensures that the accuracy and error metrics are appropriately contextualized, considering each country's dataset's unique characteristics and complexities. Consequently, the study will yield valuable and region-specific findings, contributing to a more comprehensive understanding of the analysis models' performance in diverse socio-cultural settings.

Table 1 Calculation of Accuracy Rate and Classification Errors for the Entire Dataset across Chosen Nations

ALL SELECTED COUNTRIES		
ANALYSIS MODEL	**ACCURACY LEVEL (%)**	**TYPE ERROR (%)**
ALTMAN	65.31%	34.69%
SPRINGATE	47.50%	**52.50%**
OHLSON	64.69%	35.31%
ZMIJEWSKI	74.06%	25.94%
GROVER	**78.44%**	21.56%

The business world often turns to financial models to predict a firm's future solvency, performance, or other metrics of interest. Our recent evaluation analysed five models – Altman, Springate, Ohlson, Zmijewski, and Grover – based on their accuracy levels and type errors. Through this comparative study, the efficacy of each model becomes clear, aiding in selecting appropriate tools for financial decision-making.

Among the five models assessed, the Grover model stands out, boasting the highest accuracy level of 78.44%. In financial modelling, accuracy can be a determinant of trustworthiness. With nearly 8 out of 10 predictions proving correct, stakeholders can place considerable faith in the Grover model's output. This high accuracy suggests that the model accounts for a broader range of variables or integrates a more sophisticated algorithmic approach.

On the other end of the spectrum, the Springate model's performance left much to be desired. With an accuracy level of only 47.50%, it was the least precise of all models tested. More worryingly, it also had the highest type error percentage at 52.50%. Such a high type error indicates that most of its predictions could be false positives or negatives. This can be particularly problematic, as relying on this model could result in significant financial missteps.

The remaining three models – Altman, Ohlson, and Zmijewski – offer accuracy levels between 64.69% and 74.06%. While they do not match Grover's impressive accuracy, they present a reasonably reliable picture nonetheless. Notably, Zmijewski's model edges closer to Grover's with an accuracy of 74.06%, making it the second most accurate model in the evaluation. Its type error, at 25.94%, is also relatively lower than most, rendering it a solid alternative choice.

Conclusion, in the realm of financial modelling, the right tool can make a world of difference. As demonstrated in this study, while the Grover model emerges as the leader in accuracy, other models, such as Zmijewski's, also hold promise. Meanwhile, the Springate model's performance serves as a reminder to continually scrutinize and validate model outputs before making impactful decisions. As the financial landscape evolves, it is imperative to re-evaluate these models, ensuring they remain relevant and reliable in an ever-changing economic climate.

In the dynamic realm of finance, accurate predictive models are pivotal in aiding decision-makers to navigate uncertain terrains and make informed choices. This report delves into a comparative analysis of the accuracy and error rates across five financial models in three distinct countries: Indonesia, Thailand, and Malaysia.

Table 2 Accuracy and Error Rates by Country

ANALYSIS MODEL	ACCURACY LEVEL (%)		
	INDONESIA	THAILAND	MALAYSIA
ALTMAN	51.25%	60.00%	70.00%
SPRINGATE	30.00%	44.00%	27.50%
OHLSON	47.19%	74.67%	57.50%
ZMIJEWSKI	55.63%	**78.67%**	**91.25%**
GROVER	**61.25%**	73.33%	73.75%

The models assessed include Altman, Springate, Ohlson, Zmijewski, and Grover. The results revealed that market conditions and economic environments in each country heavily influence the performance of these models. There are significant variations in accuracy levels and type errors from one model to another and from one country to another.

In Indonesia, the analysis revealed that the highest accuracy level is achieved by the Grover model by 61.25%. The Zmijewski and Altman model exhibited moderate accuracy with a rate of 55.63% and 51.25%. The Ohlson and Springate model demonstrated low accuracy at 47.19%and 30.00%.

In Thailand, the analysis revealed the highest accuracy level is reached by the Zmijewski model by 78.67%, Ohlson and Grover Models achieving accuracy rates 74.67% and 73.33% making them more reliable in the Thai market. Altman and Springate model demonstrated low accuracy at 47.19%and 30.00%.

In Malaysia, the analysis revealed The Zmijewski model was the most accurate model with 91.25% accuracy. **Grover and Altman** model exhibited good accuracy with a rate of 73.75% and 70.00%. **Ohlson** model exhibited moderate accuracy with a rate of 57.50% but Springate model demonstrated the weakest performance with 27.50%low accuracy

This analysis underscores the substantial impact of context on the performance of financial models. While some models exhibit consistent performance across countries, others need help maintaining accuracy and managing type errors in diverse markets. The triumph of the Zmijewski model across countries emphasizes its robustness, while the erratic performance of the Springate model serves as a cautionary tale. Furthermore, the report highlights the potential of the Ohlson model in Thailand and the Altman model in Malaysia.

As organizations rely increasingly on data-driven insights, understanding financial models' nuanced strengths and weaknesses across different countries becomes paramount. This report provides valuable insights into making informed decisions, minimizing potential risks, and maximizing opportunities in an ever-evolving financial landscape.

Analysis of various financial models across different countries underscores their potential to predict financial distress. While each model exhibits varying degrees of accuracy and error rates, their collective ability to provide insights into potential economic challenges remains evident. The study emphasizes that carefully considering context and model strengths, businesses can leverage these tools to effectively make informed decisions and navigate the complexities of financial landscapes.

DISCUSSION OF RESEARCH FINDINGS

The analysis revealed varying degrees of accuracy, painting a nuanced picture of each model's predictive prowess. While some models excelled in certain countries, others faced challenges, underlining the significance of context in financial predictions.

The research findings spotlight the distinct attributes characterizing each predictive model, yielding valuable insights into their relative performances. These disparities accentuated the pivotal role of model selection in concordance with specific market dynamics. However, an intriguing facet worth further exploring pertains to these performance differentials' origins. Indeed, within the realm of financial distress prediction, the disparities in scores or values that engender disparate forecasts stem from the divergent formulas underpinning each model's predictive calculus.

As the research expedition ventured into the methodologies of the Altman Z-Score, Springate, Ohlson, Zmijewski, and Grover models, it was akin to traversing distinctive avenues within the landscape of financial analysis. Each model presented a unique framework for apprehending financial distress. Springate, for instance, exhibited acumen in detecting intricate patterns embedded within liquidity and leverage markers. Conversely, the Altman Z-Score relied on a structured composition of financial ratios, each endowed with particular weights. On the other hand, Ohlson and Zmijewski amalgamated quantitative metrics with qualitative insights, incorporating market sentiment and managerial decisions. The Grover model introduced an innovative dimension, harnessing artificial intelligence to process voluminous datasets and discern patterns that might elude conventional models.

The divergent methodologies naturally translated into divergent prognoses. These models, akin to distinct tools in a craftsman's workshop, each possessed specific attributes best suited to particular scenarios. The Altman Z-Score's sensitivity to detailed financial ratios might render it adept at capturing nuanced signals.

Thus, as authors scrutinize the Altman Z-Score, Springate, Ohlson, Zmijewski, and Grover models, it becomes evident that the diversity in methodologies translates into divergent predictions of financial distress. The significance lies in discerning the essence of these differences and leveraging them to craft forecasts attuned to specific contextual nuances. This equips us with a compass, guiding us through the labyrinthine corridors of financial forecasting and arming us with the understanding to navigate with precision and foresight.

The comprehensive evaluation across countries and years pinpointed the model that consistently showcased the highest accuracy levels. The results had implications extending beyond academic curiosity, guiding practitioners and decision-makers towards more dependable financial assessments.

In wrapping up, this study sheds light on the dynamic dance between predictive models and the intricate world of financial distress within the tourism and transportation sectors. As a researcher embarked on this research journey, it became evident that each model has strengths and advantages. However, what is fascinating is how these strengths interweave with each country's unique economic and market intricacies. These findings not only contribute to academic conversations but also offer practical guidance. They become a navigational guide for businesses and investors, steering them through the complex waters of financial uncertainty, armed with insights from the Altman, Springate, Ohlson, Zmijewski, and Grover models.

Based on comprehensive research that has been conducted, author has identified a particular model that distinctly stands out due to its superior accuracy levels and minimal error rates, which is the Grover Model. This model can be confidently deemed as the most reliable and robust tool for analyzing the potential of financial distress within a corporate setting. It's worth noting that this model's performance has been benchmarked against several others, consistently proving its efficacy in such critical financial analyses. Its application in the field can significantly enhance the predictability and understanding of financial challenges that companies might face.

CONCLUSION

The core objective of this research was to delve into the realm of financial distress within the context of the transportation and tourism industries. Employing the Altman Z-Score, Springate, Ohlson, Zmijewski, and Grover models, the study aimed to meticulously analyze the financial health of companies listed on the Indonesian Stock Exchange, Malaysia Stock Exchange, and Thailand Stock Exchange. The time frame for this exploration spanned from 2018 to 2022, encapsulating a dynamic period marked by market volatility and significant global events. In total, 64 companies formed the basis of the study's sample, ensuring a robust and comprehensive examination. Based on this research, it can be concluded that: The Grover Model achieved the highest accuracy scores across the selected countries and In the country-specific investigations, Zmijewski's predictive accuracy emerged as the most reliable for Malaysia and Thailand but In Indonesia, Grover outperformed the other models in terms of predictive accuracy.

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