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Predicting Financial Distress Using DEA and Multivariate Discriminant for Tourism, Restaurant, and Hotel Sector in Indonesia

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ABSTRACT

Financial distress is a condition in which a company experiences decline and difficulty to fulfil its financial obligations. Financial distress prediction aims to identify early warning indicators of impending financial disaster so businesses can begin financial reconstruction at the appropriate moment. This study aims to compare the statistically significant difference results of various financial prediction models and the level of accuracy of each model in 25 companies engaged in the hotel, restaurant, and tourism sectors in 2018-2021. By using Kruskal-Wallis Test, Mann-Whitney Post Hoc Test, and accuracy test to compare each model. The results of this study are based on the Kruskal-Wallis test, all models used are statistically significant differences. Meanwhile, when paired using the Mann-Whitney Post-Hoc Test, it was found that the Springate and Grover models did not have a statistically significant difference. In addition, the results of the test accuracy show that the DEA accuracy rate of 79%, and the Springate model with the lowest accuracy of 33%. The results interpret that each model has its own indicator in predicting financial distress. It recommended in examining the financial distress of hotel, restaurant, and tourism companies using DEA model, since it results the highest accuracy rate.

Keywords: DEA, Financial Distress, Multivariate Discriminant Analysis.

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INTRODUCTION

In December 2019, a mysterious infectious disease, caused by acute respiratory syndrome and characterized by fever, cough, fatigue, and a loss of sense of taste or smell–now known as the Covid-19 outbreak has hit the whole world (Wu, Chen, & Chan, 2020). About 95% of countries in the world experienced negative economic growth and crisis like no other. Gross Domestic Product (GDP) is one of the indicators that is often used to show a country's economic growth. Covid-19 has had a detrimental influence on international economic growth and some countries, as shown in Figure 1., based on annual GDP per capita growth.

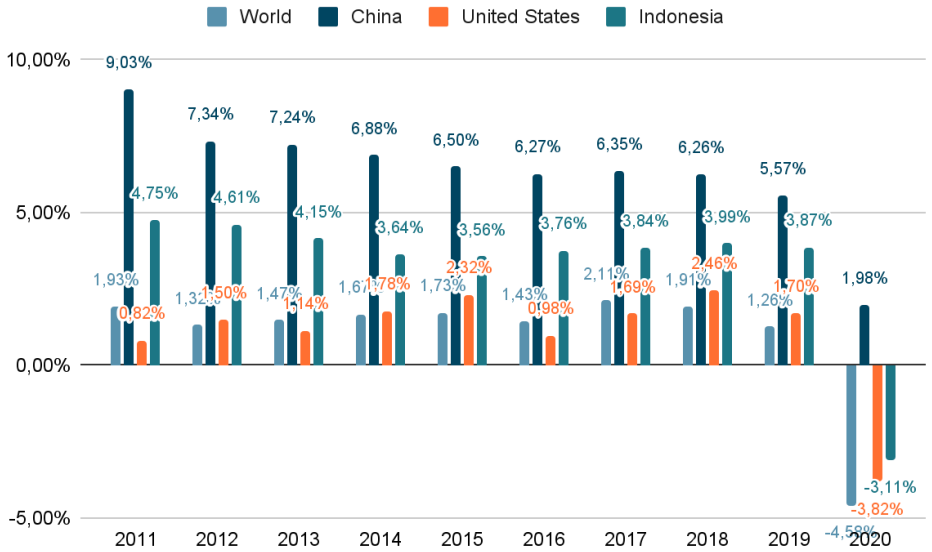
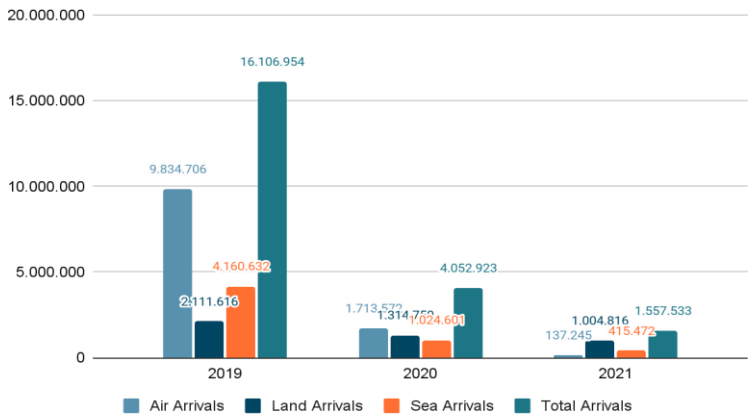


Figure 1. Annual Growth of GDP per capita, 2011 – 2020 (Source: World Bank and OECD)

In the tourism sector, the COVID-19 has a substantial influence on business as it is the most affected sector by the pandemic (Espinoza et al., 2021). Meanwhile, specifically, the tourism sector before the pandemic accounted for 10.6% of the total number of jobs in the world, 10.4% of global GDP, and 30% of global trade in services (WTTC, 2021). Unfortunately, this sector is very sensitive to crisis events, such as pandemics, terrorism, natural disasters, because when this news emerged, tourists immediately decided to cancel or postpone their trips.

This is what happened to the hotel, restaurant, and tourism industries in the midst of the Covid-19 outbreak, especially when the Large-Scale Social Restrictions (PSBB) in Indonesia were enforced. This has caused the number of domestic and international tourists, hotel occupancy rate, and restaurant visitors to be declining.



Source: The Central Bureau of Statistics (BPS)
Figure 2. Tourist Arrivals in Indonesia 2019 – 2021

The importance of the tourism sector in Indonesia, apart from being a contributor to foreign exchange and employment, also creates a multiplier effect on the growth of other sectors. With the presence of the pandemic, Indonesia's tourism sector has been the worst hit and its recovery will take quite a long time. This is certainly difficult for the government, which has set ambitious targets to make the tourism sector a contributor and a strategic role (Kemenparekraf, 2020).

Therefore, it is critical to carry out periodic assessments to determine the likelihood of financial difficulties, which could lead to insolvency, and to forecast a company's viability. The authors are interested in undertaking an analysis of financial distress in the hospitality, culinary, and tourist industries in Indonesia based on the results of the foregoing explanation. Financial distress occurs when the company's activities are inadequate resulting in insufficient company obligations (insolvency) (Septiani, Siswantini, & Murtatik, 2021). The goal of financial distress prediction is to identify early warning indicators of impending financial disaster so that businesses can begin financial reconstruction at the appropriate moment.

There are many analytical methods that have been developed and used to measure financial distress, namely: Springate analysis, Zmijewski analysis, Grover analysis, and Altman analysis. However, no previous study has shown the consistency of accuracy results or which model provides the highest accuracy. Yendrawati and Adiwafi (2020) concluded that in comparison to other models (Zmijewski and Springate), the Z-Score model has the best level of accuracy. However, Prasetianingtias & Kusumowati (2019) claim that the Grover model has the greatest level of accuracy when compared with Springate, Altman, and Zmijewski. Moreover, the research finding of Setiawan & Diana (2020), compared the predicted accuracy of the Altman Z-Score with the new prediction model, DEA, and discovered that DEA outperforms the Altman Z-Score.

A drop in financial performance caused by external and internal variables may be an indicator of a drop in corporate efficiency before it causes financial difficulty. This is a consideration for several researchers regarding the relationship between financial distress and company efficiency (Setiawan & Diana, 2020). DEA is a non-parametric method based on linear processing that is used to evaluate the relative efficiency of analytical units known as Decision Making Units (DMUs) (Wulandari, 2016). The application of the Data Envelopment Analysis (DEA) model will be used to assess indication of business failure. This model usually provides its own advantages in processing small samples.

Given the foregoing, the authors planned to carry future studies related to the comparison of the application of the bankruptcy prediction model between the S-Score, X-Score, G-Score, Z-Score, and Data Envelopment Analysis (DEA) and its accuracy level of the hospitality, culinary, and tourist industries prior and in the time of pandemic.

LITERATURE REVIEW

Financial Distress and Bankruptcy

Based on Bankruptcy Data, the term bankruptcy comes from the Latin, namely bancus which means “bench or table” and ruptus which means “broken”. Furthermore, according to Onakoya & Olotu, bankruptcy occurs when a corporation is unable to generate enough revenue to cover its costs, implying that the company has a negative economic worth. Besides, in Australia, France, and Germany, bankruptcy is defined as a legal word that refers to a company’s inability to meet its financial commitments. On time so business operations are terminated, and the company is liquidated to meet creditors’ claims (Farooq, Jibran Qamar, & Haque, 2018).

Depending on the definitions above, it can be said that bankruptcy begins with financial difficulties which indicate that the corporation is having financial distress that cannot be helped. According to Indriyanti (2019), financial distress refers to a situation where the company is in difficulty and cannot fulfil its financial obligations for several reasons such as high expenses, deficiency of liquid assets, and the occurrence of an economic downturn resulting in decreased revenue. Moreover, Puro et al., (2019) compared financial distress as a period when the company cannot pay its debts to lenders, and bankruptcy as an official statement of the cessation of business activities due to unresolved financial difficulties.

The insolvent company can occur due to external or internal factors (Husein & Pambekti, 2015). Internal factors arise from poor financial management and performance such as accounts receivable that are too large to customers causing bad company efficiency, low quality of the company’s human resources, lack of working capital, volatility of earnings, to corruption, collusion, nepotism, and fraud among company executives can cause problems for the business. Apart from it, external factors emerge as a result of economic conditions and the business environment such as inflation, interest rates, crises due to natural disasters, and unfavorable political conditions of a country. Therefore, financial distress is not the only factor that causes bankruptcy and not all financial difficulties end in bankruptcy (Setiawan & Diana, 2020).

Financial Distress Prediction Model

Many studies have been conducted by researchers to identify early warning indicators of financial distress experienced by companies. This is due to the importance of bankruptcy risk prediction on corporate governance so that various analytical models are developed. Each model has its advantages and disadvantages, as well as the level of accuracy. These predictive accuracy and performance factors depend on the predictor set, sample, and classification technique (Nur & Panggabean, 2020).

Springate S-Score

Gordon L.V Springate first developed the Springate analysis model at Simon Fraser University. The Altman Z-Score model developed with MDA has been updated by this model. Meanwhile, Gordon uses 19 ratios with 40 sample companies to get four ratios to predict potential bankruptcy. The results of his research resulted in an accuracy rate of up to 92.5%. The Gordon model formula (S-Score) is as follows:

$$S = 1{,}03X1 + 3{,}07X2 + 0{,}66X3 + 0{,}4X4 \quad (1)$$

Details:
X1 = Working Capital / Total Assets
X2 = EBIT / Total Assets
X3 = EBIT / Current Liabilities
X4 = Sales / Total Assets
where this model offers a criterion for determining if a corporation is healthy or bankrupt:

- S-Score less than 0,862 is categorized as bankrupt
- S-Score more than 0,862 is categorized as not bankrupt

Zmijewski X-Score

In 1984, Zmijewski employs probit analysis to examine a bankruptcy prediction model in which the ratios of profitability, liquidity, and financial leverage were included. Uniquely, this model uses a ratio of 1:20 in six data sets, where there are 40 enterprises that have gone bankrupt and 800 that are still in business. There is also a “basic choice” sample bias and a “sample selection” bias in this model. The X-Score formula is written below:

$$X = -4{,}3 - 4{,}5X1 + 5{,}7X2 - 0{,}004X3 \quad (2)$$

Details:
X1 = EAT / Total Assets
X2 = Total Debt / Total Assets
X3 = Current Assets / Current Liabilities
where the standard of this model is classified as follows:

- X-Score less than 0 or negative is categorized as healthy
- X-Score more than 0 or positive is ccategorized as bankrupt

Grover G-Score

Jeffrey S. Grover performed a restoration of the Altman Z-Score prediction model by using each of the 35 bankrupt and non-bankrupt companies and adding 13 new ratios. This model continues to use the X1 and X3 Altman Z-Score models and then adds the ROA ratio. The model is written with the formula:

$$G = 1{,}65X1 + 3{,}404X2 - 0{,}016X3 + 0{,}057 \quad (3)$$

Details:
X1 = Working Capital / Total Assets
X2 = EBIT / Total Assets
X3 = EAT / Total Assets
where the standard of this model is classified as follows:

- G-Score more than 0,01 is classified as not bankrupt
- G-Score less than -0,02 is classified as bankrupt

Altman Z-Score

Altman Z-Score developed by Edward I. generates 5 ratios from 33 pairs of bankrupt and non-bankrupt enterprises and 22 ratios. The Z-Score formula is written as follows:

$$Z = 1{,}2X1 + 1{,}4X2 + 3{,}3X3 + 0{,}6X4 + 0{,}999X5 \quad (4)$$

Details:
X1 = Working Capital / Total Assets
X2 = Retained Earnings / Total Assets

X3 = EBIT / Total Assets
X4 = Market Value of Shares / Total Debt
X5 = Sales / Total Assets
where the standard of this model can be classified as follows:

- Z-score more than 2.675 is categorized as healthy
- Z-Score between 1.81 to 2.675 is categorized as a grey zone
- Z-score less than 1.81 is categorized as bankrupt

Data Envelopment Analysis (DEA)

Data Envelopment Analysis is a technique for determining the degree of efficiency of Decision-Making Units (DMU) in a company. Where the method, which was first introduced by Charnes, Cooper, and Rhodes (1978) utilizes various resources (inputs) to obtain output. DMU can be measured by applying a non-parametric frontier estimation method by comparing it with the existing efficiency frontier.

This non-parametric method has in recent years expanded its use not only to measure efficiency but also to assess indications of a company's bankruptcy. But keep in mind that the use of methods in the two cases is different. The popularity of the DEA for assessing indications of corporate bankruptcy in recent years is due to the following reasons (Araghi & Makvandi, 2013):

- Possibility of assessing infinite and complex relationships between various inputs and outputs.
- Does not require large data samples.
- There is no need to estimate the shape of the function in analyzing financial ratios and their distribution ratios.
- As for Charnes et al. (1978) claim several points that make DEA an interesting new method for analyzing data, namely:
- Focuses on observing individuals who differ from the population mean
- Can utilize inputs and outputs in generating a single aggregate size for each DMU
- Its inputs and outputs do not require the declaration of weights or costs.
- The function of the producing relations has no restrictions.
- Able to give precise estimates of changes in input and output as needed to measure DMU from below the efficient frontier to above the efficient frontier.

RESEARCH METHOD

This study applies a quantitative technique to collect measurable data, which is then analyzed using tools. To produce information to meet the research goals, researchers must employ a technique known as sampling design, which assists the researchers or authors of this study in defining the sample of the study.

The sample criteria used in this study are as follows:

- Companies engaged in the hospitality, culinary, and tourist industries and listed on the Indonesia Stock Exchange during the 2018-2021 period, respectively.
- Hospitality, culinary, and tourist industries companies that publish complete financial statements for the 2018-2021 period.

According to the criteria given, 25 companies out of 44 companies engaged in hospitality, culinary, and tourist industries will be selected as sample. Furthermore, the data that will be used spans the year 2018 – 2021. The total observation data is 100.

Data Analysis Method

Descriptive Statistics

Descriptive statistics provide general information about the variables being tested in the research (Purwanto & Agustin, 2017). Descriptive statistics are method for gathering, summarizing, presenting, and interpreting data by describing the relationship between observable variables or population. According to Weiss (2012), there are several descriptive measures, such as the mean, maximum and minimum values, and standard deviation, that may be calculated to help organize and describe data.

Kruskall-Wallis Test

According to Priyatno (2013), the Kruskal Wallis Test is a ranking-based non-parametric test that determines whether there are statistically significant differences between two or more groups of independent variables on the dependent variable on a numerical data scale (interval or ratio) and ordinal scale. This test permits the normality assumption to be disobeyed and eliminates the requirement for a normality test.

The null and alternative hypotheses for the Kruskall-Wallis test in this study are as follows:

H_{01} : There is no significant difference among Springate S-Score, Zmijewski X-Score, Grover G-Score, Altman Z-Score, and DEA model to predict financial distress in the hospitality, culinary, and tourist industries in Indonesia for the period 2018 – 2021.
If the value > 0,05, H01 is accepted.

H_{a1} : There is a significant difference among Springate S-Score, Zmijewski X-Score, Grover G-Score, Altman Z-Score, and DEA model to predict financial distress in the hospitality, culinary, and tourist industries in Indonesia for the period 2018 – 2021.
If the value < 0,05, H01 is rejected.

Data Envelopment Analysis

Researcher in this study predict financial difficulty using the DEA method. Essentially, the DEA model compares the input and output data with other input and output data from comparable DMUs. The construction of the production model is the most significant component of the DEA analysis. It must accurately depict the actual process and take into consideration the most critical inputs and outputs.

The variables that will be applied to this model are Total Assets and Total Liabilities as inputs or indications of company wealth, while the outputs are EBIT, Retained Earnings, Working Capital, and Market Capitalization which indicate stakeholder perceptions of the company. The input used is considered to be a reference for companies with a certain market value, what is the smallest asset base that can produce a certain level of profit.

Hypotheses Test

Post Hoc Test

According to Acebeli (2020), post Hoc test is a follow-up test after a different test. The Post Hoc test is carried out if there is a substantial difference between the independent variables. If the data is normally distributed, the Post Hoc test performed is the Posy Hoc ANOVA Test. However, the Mann Whitney U-Test is used for nonparametric testing when the data is not regularly distributed. In the research of Setiawan and Rafiani (2021), Mann Whitney was employed as a post hoc test for the Kruskall-Wallis comparison test to gain more specific information. The Mann-Whitney test is a non-parametric test that is used to determine the difference in the median or average of two independent groups for dependent variable data with an ordinal or interval/ratio scale but does not meet the assumption of normality (Nachar, 2008).

Accuracy Test

The accuracy test is used to assess the accurate and wrong predictions based on the actual financial situation of the selected samples. In this study, the accuracy rate is employed to quantify the amount of prediction capability. The more precise the model, the better the model's prediction ability. Using each model cut-off point as shown in Table 3.4, the researchers begin by computing the predicted outcome in each sample and labelling their position as stable or distressed. The following formula is used to compute the accuracy rate:

$$Accuracy\ rate = \frac{The\ number\ of\ correct\ prediction}{Total\ number\ of\ sample} \times 100\% \quad (5)$$

Table 2. Cashflow Pattern as Cut-Off Point for Stable & Distress Company Indication

Financial Condition	Financial Position			
	Earning	Cashflow Activities		
		Operating	Investing	Financing
Stable	+	Cash flow pattern none mentioned in group 1		
	-	+	-	-
	-	-	-	+
	-	-	+	+
	-	-	+	-
Distress	-	+	+	-
	-	+	-	+
	-	-	-	-

Adjusted by Researcher, 2022

RESULTS

In table, it shows the descriptive statistics analysis of each model of this study.

Table 3. Descriptive Statistics (*N* =100)

Model	N	Minimum	Maximum	Mean	Std. Deviation	Variance
S_Score	100	-2.74	1.83	0.2338	0.72303	0.523
X_Score	100	-4.80	1.73	-1.9880	1.35782	1.844
G_Score	100	-1.27	1.33	0.1771	0.40221	0.162
Z_Score	100	-0.73	2390.06	51.6096	289.85085	84013.514
DEA	100	0.00	1.00	0.7872	0.30302	0.092
Valid N	100					

Table 3 shows:

a. The lowest score of Springate model is -2.74 and the highest score is 1.83. The score of 0.2338, 0.72303, and 0.523 show the average score, standard deviation, and variance of Springate Model.
b. The score of -4.80 and 1.73 is the minimum and maximum score of the Zmijewski analysis of the 100 observations data. The average score is -1.988, while the standard deviation and variance are 1.35782 and 1.844.
c. The lowest score of Grover model is -1.27 and the highest score is 1.33. The average score, standard deviation, and variance are 0.1771, 0.40221, and 0.162.

d. The score of -0.73 and 2390.06 is the minimum and maximum score of the Altman Z-Score. The score of 51.6096, 289.85085, and 84013.514 is the average value, standard deviation, and variance of this model on the 100 observations data.
e. The lowest score of DEA is 0 and the highest score is 1. The average score, standard deviation, and variance are 0.7872, 0.30302, and 0.092.

Table 4. Kruskal-Wallis Test Statistics

Item Name	Model
Kruskal-Wallis H	313.157
Df	4
Asymp. Sig	0.000

From the table of the results of the Kruskal Wallis test, it is known that the Asymp value. Sig. 0.000, so Asymp. Sig. 0.000 < 0.05, which means that the hypothesis is accepted that there is a significant difference between the five financial distress methods used in this study (H_{a1} is accepted).

Table 5. Mann-Whitney U Test Result

No	Paired Model	Mann-Whitney U	Z	Asymp. Sig (2-tailed)
Pair 1	Springate – Zmijewski	870.50	-10.090	0.000
Pair 2	Springate – Grover	4817.50	-0.446	0.656
Pair 3	Springate – Altman	1170.50	-9.357	0.000
Pair 4	Springate – DEA	2276.50	-6.707	0.000
Pair 5	Zmijewski – Grover	768.00	-10.341	0.000
Pair 6	Zmijewski – Altman	194.5	-11.742	0.000
Pair 7	Zmijewski – DEA	337.5	-11.482	0.000
Pair 8	Grover – Altman	888	-10.047	0.000
Pair 9	Grover – DEA	1146	-9.492	0.000
Pair 10	Altman – DEA	2074.5	-7.208	0.000

To analyze which financial distress group has a significant difference, a Post-Hoc Test is needed, namely using the Mann-Whitney Test. Based on the results of the Mann-Whitney test above on 5 models of financial distress in this study, it can be summarized that all paired model has significant difference because of the Asymp. Sig is lower than 0.05, except Springate and Grover that has no significant difference based on this test.

Table 6. The Overall Accuracy Rate of Multivariate Analysis and DEA in Predicting Financial Distress

Model	Total Sample	Number of Correct Prediction	Accuracy Rate
Springate S-Score	100	33	33%
Zmijewski X-Score	100	74	74%
Grover G-Score	100	69	69%
Altman Z-Score	100	43	43%
DEA	100	79	79%

The accuracy test is used to assess the accurate and wrong predictions based on the actual financial situation of the selected samples. Based on the results of the analysis above, Springate has the accuracy level of 33%, Zmijewski 74%, Grover 69%, Altman 43%, and DEA 79%.

DISCUSSION

The financial distress prediction models utilized in this analysis are known as Multivariate Discriminant Analysis, which employs two or more ratios in one equation to facilitate the analysis of a company's financial condition. The results of calculations using the Springate S-Score method on 25 companies engaged in the Hotel, Restaurant, and Tourism sector from 2018 – 2021 show that most companies have experienced distress since 2018. While, based on the results of calculations using the Zmijewski X-Score method which has a cut-off point equal to or less than 0 indicated as healthy, most companies do not experience financial difficulties. In the Grover G-Score method, these 25 hotel, restaurant, and tourism sector companies from 2018 – 2021, most of them are categorized as not experiencing financial distress. Compared to Altman during the period 2018 – 2021, most of the companies are categorized as healthy and are in the grey zone (an indication of bankruptcy in the near future). DEA scores were generated for 25 companies in 2018 – 2021 using the input orientation method based on the VRS assumption model. Based on previous research conducted by Setiawan and Diana (2020), 0.66 is the optimal cut-off point which implies company score above 0.66 is assumed to be healthy, and below 0.66, the company is experiencing financial distress.

The results of the normality test show that there are data that are not normally distributed, namely the X-Score, Z-Score, and DEA, so that the difference test in this study cannot be carried out using a parametric approach through the paired t-test sample test, because it does not meet the assumptions where the data to be tested with a parametric approach must be normally distributed. Therefore, the different test in this study will be carried out with a non-parametric approach using the Kruskal Wallis test and followed by the Post Hoc Test (using the Mann Whitney Test).

This result of The Kruskal Wallis is in line with the study conducted by Ditasari, Triyono, and Sasongko (2017) and Setiawan and Rafiani (2021) who stated that there are significant differences between financial distress models, namely Springate S-Score, Zmijewski X-Score, Grover G-Score, and Altman Z-Score.

Based on Mann-Whitney Test, it shows that all paired model has significant difference because of the Asymp. Sig is lower than 0.05, except Springate and Grover that has no significant difference based on this test. This can be seen from the formula Springate and Grover both use the ratio of working capital to total assets and EBIT to total assets. In addition to the two ratios, Grover only added one variable, namely earnings after tax to total assets. As a result, the interpolation median difference between Springate and Grover will be less than that of the other groups.

Based on the results of the accuracy test, it can be concluded that the DEA prediction model gets the highest accuracy score, which is 79%, followed by Zmijewski at 74%, Grover 69%, Altman Z-Score 43%, and Springate has the lowest accuracy score, which is 33%.

CONCLUSION

Based on the analysis and interpretation in the previous analysis, the conclusions could be summarized as follows:

1. According to Kruskal-Wallis Test, there is a significant difference among Springate S-Score, Zmijewski X-Score, Grover G-Score, Altman Z-Score, and DEA (Data Envelopment Analysis) model to predict financial distress in the hospitality, culinary, and tourist industries in Indonesia for the period 2018 – 2021. This can happen because of the differences in the variables used in each prediction model.
2. Based on Mann Whitney Post Hoc Test, the test to determine which pair is significantly different, the test discovered that there is no significant different between Springate S-Score and Grover G-Score to predict financial distress in the hospitality, culinary, and tourist industries in Indonesia for the period 2018 – 2021.
3. While the results of the test accuracy show that DEA has the best accuracy rate compared to other models, which is 79% and the worst accuracy rate is the Springate S-Score, followed by Altman Z-Score models because it cannot predict accurately even up to 50% of total data (33% and 43%, respectively).
4. The critical selection of input and output variables on DEA is most likely responsible for the high accuracy rate. Working capital output, which measures liquidity and is typically related to financial health, may be likely to have a major contribution to predicting distress and contribute to an increase in accuracy rate. As a result of this discovery, the DEA model appears to be a useful tool for forecasting financial distress.

LIMITATION

This study has several limitations, such as

a. The limited data used is only in 2018 – 2021 with an annual time series from the financial statements of each company engaged in the hospitality, culinary, and tourist industries.
b. The selected sample is limited to hospitality, culinary, and tourist companies that issue audited annual financial reports.
c. Most of the prediction models are limited to several ratios/variables, namely: working capital to total assets, retained earnings to total assets, EBIT to Total Assets, and the book value of equity to total liabilities, EBIT to Total Liabilities, Sales to Total Asset.

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DECLARATION OF CONFLICTING INTERESTS

The authors affirm that they have no financial or non-financial conflicts of interest, affiliations with, or involvement in any organization or entity that might have an interest in the publication of this paper.

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