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ANALYSIS OF THE ACCURACY OF BANKRUPTCY PREDICTION MODELS: THE CASE OF LITHUANIAN COMPANIES

Jurgita Stankevičienė, Gabija Prazdeckaitė
Kaunas University of Technology, Lithuania

Abstract

The aim of this research is to analyze the accuracy of selected bankruptcy prediction models on the example of Lithuanian companies. The research involves financial statements of 23 companies that have gone bankrupt over the period of 2013-2019. We used three different groups of models. The first two are considered as classic models which were developed using discriminant analysis (Altman, modified Altman, Springate, Taffler and Tishaw, and Grover models) and logistic regression (Ohlson, Zmijewski, and Grigaravičius models). The third group is based on artificial intelligence (we used a decision tree model, which is the most innovative and the least explored model of all used). The analysis evidenced that the logistic regression models, such as Zmijewski and Ohlson, demonstrated the best results in the group of classic prediction models, i.e., high probability of bankruptcy even earlier than one year prior to actual bankruptcy in the case of most companies. However, the decision tree must be considered as the most accurate model as it predicted bankruptcy of all analyzed companies one year before actual bankruptcy; this could be interpreted as 100% accuracy. Too late bankruptcy process causes many negative consequences for company's employees, partners, and the state. Though problems with financial resources such as growing accounts payable and the shortfall of working capital which contribute to insolvency can be seen in the financial statements, in addition to the analysis of financial indicators, it is particularly important to use the above-mentioned bankruptcy prediction models, which help to detect financial problems in time and make the right decisions concerning future activities.

Keywords: bankruptcy, bankruptcy prediction models, insolvency, Lithuanian companies.
JEL Codes: G32, G33.

Introduction

Bankruptcy can be described as a legal procedure involving a business that is no longer able to repay their debts. In today's economic climate, bankruptcy is being discussed every day, as many businesses around the world suffer from activity restrains and insolvency due to COVID-19 crisis. The issue of bankruptcy was never debated as widely as it is discussed today, and the scale of financially troubled businesses due to lockdown is overwhelming. Accordingly, even though this process nowadays can occur very often, it can cause unwanted damages not only to the bankrupt business, but to all members of the society as well. The consequences of bankruptcy can be very negative to the executives of the company as well as to investors, employees, suppliers, clients, and the government (Bhutta and Regupathi, 2020). It is not that uncommon for business, that has real financial struggles, not to recognize the need for bankruptcy which leads to too late bankruptcy proceedings (Prazdeckaitė and Stankevičienė, 2020). This raises a question – can bankruptcy be a positive process for a business, that has run out of its potential, if it is implemented at the right time? The answer can be "yes", if all the factors indicate that there is no chance for going on and bankruptcy is unavoidable. It can reduce the damages to all the interested parties of the business (executives, employees, investors, etc.). Therefore, it is important to detect early signs of potential insolvency, forecast the future of the company and act on it. Additionally, the current economic situation also proposes discussions about the need of constant bankruptcy prognosis in companies. It can be argued that a great number of companies, that went or will go bankrupt due to COVID-19 crisis, might have survived assuming the crisis would have never happened (even though they might have had financial struggles) and the early prognosis of bankruptcy would have given them a chance to change the financial situation for the better one, i.e., prepare for a possible struggle and survive a crisis like this.

There are many scientific studies that explore and analyze the accuracy of bankruptcy prediction models. Nevertheless, one of the most analyzed bankruptcy prediction models was created by Edward I. *Altman* in 1968 and introduced a discriminant analysis methodology using financial indicators (Kansal and Sharma, 2019). The well-known scientist analyzed more than 20 financial indicators using multivariate discriminant analysis and selected 5 most suitable indicators that can signalize the potential insolvency. Using these indicators, a Z score is being calculated, which shows the potential level of bankruptcy (Hassan et al., 2017). Gunawan et al. (2017) analyzed the Z score method in their study using the financial statements of manufacturing companies. The results evidenced, that Altman score is accurate. Other authors, such as Aminian et al. (2016) compared Altman model to others and found that all of them demonstrate high accuracy and can be used to forecast bankruptcy. Muñoz-Izquierdo et al. (2020) found that Altman Z score can predict bankruptcy with a high accuracy (75%) and stated that their findings are the same as that of many other studies done before. Prabowo (2019) stated that Z score can be used as an accurate tool in insolvency forecasting as well. Mohd Johari et al. (2019) analyzed Nokia and Samsung companies and calculated standard mean errors. They analyzed several methods and their results evidenced that Altman models' standard error of the mean was the lowest and this method is the best for bankruptcy prediction. Yoewono (2018) studied financially healthy as well as already bankrupt companies and found that Altman model demonstrated the lowest deviation for prediction of already bankrupt companies, i.e., out of 4 analyzed models, Altman showed the best results. Altman model was found as accurate in the studies of Mackevičius and Silvanavičiūtė (2006), Pakdaman (2018) as well. Putri (2018) analyzed financial indicators of only one not bankrupt company during the period of 2011-2016 and compared 5 different models. Contrary to the results of previous studies, the Altman model was the least accurate here and predicted that company is supposed to go bankrupt. Kanapickienė and Marcinkevičius (2014) found the lower accuracy in the case of Lithuanian companies as well. As less accurate Altman model was named by Imelda and Alodia (2017). Thus, it can be concluded that although the Altman model is one of the oldest, it is often considered as one of the most accurate and suitable for predicting bankruptcy; nevertheless, the results in individual cases may be contradictory as well.

Even though Altman model is one of the most popular and considered to be accurate, academics are always on a search for an improvement. Taking this into account, a *modified Altman* Z score model was implemented. Puro et al. (2019) used this model to analyze the financial statements of 53 bankrupt ad 53 not bankrupt companies (other two models were also used in the study). The results evidenced that modified Altman Z score accurately forecasted the insolvency of 49 enterprises out of 53 (the ones which have went bankrupt) and it forecasted that 45 out of 53 non-bankrupt companies are financial healthy. That means, the model predicted the right fate of 94 companies out of 106. Accordingly, it can be stated that described model have evidenced fairly accurate results in the past and can be used as a prediction tool. As highly accurate, this model was named by Syamni et al. (2018) as well.

Another widely used model – *Springate* – was based on that of Altman. The model was implemented in 1978 by Gordo LV Springate and is made up using multivariate discriminant analysis. Springate analyzed 19 financial indicators and chose 4 of them as best representing the financial state of a company (Husein and Pambekti, 2014). Putri (2018) found that the accuracy of this model was more that 92%. High accuracy of this model was established by Mackevičius and Silvanavičiūtė (2006), Pakdaman (2018) as well. Even though Springate is considered as an accurate model for forecasting, there are also some negative findings concerning it. For example, Aminian et al. (2016) and Yoewono (2018) found that this model is less accurate if compared to previously discussed Altman model. Kanapickienė and Marcinkevičius (2014) also named this Springate model among less accurate, but also suitable for bankruptcy prediction. However, Tristanti and Hendrawan (2020) found that the Springate and Altman models give similar results and the potential bankruptcy in the future may be caused by the lack of working capital. Some authors notice that similar results may be obtained because of similarity of these models.

The authors of *Tafller and Tishaw* model wanted to design a tool that would identify the potential of a companies' continuity – they analyzed 46 enterprises that have already went bankrupt as well as 46 healthy and operating companies. Authors analyzed 80 different financial indicators and selected only 4 that most accurately predicted bankruptcy (Mackevičius and Silvanavičiūtė, 2006). Contrary to the previous models, it should be noted that Tafller and Tishaw model is little explored, moreover, the researchers obtained contradictory results. Mackevičius and Silvanavičiūtė (2006) analyzed the financial statements of Lithuanian manufacturing companies during the period of 2000-2004 and found that Taffler and Tishaw model was one of the most accurate. However, the results of Kanapickienė and Marcinkevičius (2014) and Krušinskas et al. (2014) who also analyzed Lithuanian companies and their potential to survive or to go bankrupt were different. Thus, it is evident that different studies can give completely different results and there is not enough information whether the Taffler and Tishaw model is applicable and accurate.

Another method is *Grover* bankruptcy prediction model. Grover used Altman model to come up with a new one – he analyzed financial indicators of 70 enterprises (35 of them were bankrupt and 35 were not), added 13 more indicators to those used by Altman and after the research created a model with 3 indicators (Hantono, 2019). Syamni et al. (2018) analyzed several different bankruptcy prediction models and found that the Grover model was the least accurate. As not very accurate, the Grover model was named by Yoewono (2018) as well. Though this model forecasted that all the companies, which have not gone bankrupt, are healthy (100% accuracy), the prediction of bankruptcy for insolvent companies was not so accurate – only 42%. On the contrary, Pakdaman (2018) researched the accuracy of several bankruptcy prediction models in Teheran stock-exchange market and found that the Grover model had the highest coefficient of determination (0.98). It means, that Grover model is the most suitable for bankruptcy prediction. As accurate, Grover model was also named by Aminian et al. (2016), Putri (2018), Gunawan et al. (2017).

One of the first logistic regression bankruptcy prediction models, *Zmijewski* model was developed in 1983 (Prabowo, 2019). The author of the model used F test for particular groups of financial indicators and the financial information of 40 bankrupt and 800 financially healthy companies. The results evidenced 84.14% accuracy (Aminian et al. 2016). Gunawan et al. (2017) analyzed the state of "stress" in 110 firms listed in Indonesian stock exchange market in 2014. The results evidenced that three methods can be used to detect "stress" in companies, but the Zmijewski model demonstrated the highest accuracy. Husein and Pambekti (2014) also analyzed the accuracy of Zmijewski model and the results evidenced that this model is the right choice for bankruptcy prediction. The same conclusions were made by Putri (2018). However different results were obtained by Yoewono (2018) and Pakdaman (2018), who found that accuracy of Zmijewski model was low.

Another logistic regression model, the *Ohlson* model is also used widely to detect early signs of insolvency. Imelda and Alodia (2017) used Ohlson model in their study for the analysis of Indonesian stock exchange market companies and the results evidenced that Ohlson model is more accurate if compared to Altman model. As accurate, the Ohlson model was also named by Putri (2018), Syamni et al. (2018). On the contrary, Mohd Johari et al. (2019) predicted bankruptcy for Nokia and Samsung companies and found that the Ohlson model was the least accurate if compared to other models (the highest error was quantified).

Grigaravičius is the only discussed Lithuanian model. The accuracy of this model was analyzed by Butkus et al. (2014) and the results were high – 84% accuracy. Nevertheless, the authors suggest that model has flaws because of the calculation of the formula.

Nowadays widely used bankruptcy prediction model of artificial intelligence is the *decision tree* model. Gepp et al. (2010) analyzed this model and the results evidenced that this model is more accurate than others therefore it should be used for the bankruptcy prediction. Krušinskas et al. (2014) recommended to use this model in the case of economy growth.

On the ground of scientific literature, it can be stated, that every model has its advantages and disadvantages, and the results of their accuracy are controversial (see Table 1).

Table 1. The Accuracy of Bankruptcy Prediction Models in Scientific Literature

Model	Accuracy		
	Highest	Acceptable	Lowest
Bankruptcy prediction models based on discriminant analysis			
Altman	Mackevičius and Silvanavičiūtė (2006) Mohd Johari et al. (2019) Yoewono (2018)	Aminian et al. (2016) Gunawan et al. (2017) Hantono (2019) Husein and Pambekti (2014) Muñoz-Izquierdo et al. (2020) Pakdaman (2018) Prabowo (2019)	Imelda and Alodia (2017) Kanapickienė and Marcinkevičius (2014)
Modified Altman	Puro et al. (2019) Syamni et al. (2018)		
Springate	Mackevičius and Silvanavičiūtė (2006)	Aminian et al. (2016) Hantono (2019) Husein and Pambekti (2014) Kanapickienė and Marcinkevičius (2014) Pakdaman (2018) Yoewono (2018)	
Taffler and Tishaw	Mackevičius and Silvanavičiūtė (2006)		Kanapickienė and Marcinkevičius (2014) Krušinskas et al. (2014)
Grover	Aminian et al. (2016) Pakdaman (2018)	Gunawan et al. (2017) Hantono (2019) Husein and Pambekti (2014)	Syamni et al. (2018) Yoewono (2018)
Bankruptcy prediction models based on logistic regression			
Zmijewski	Gunawan et al. (2017) Husein and Pambekti (2014)	Aminian et al. (2016) Hantono (2019) Prabowo (2019) Puro et al. (2019)	Pakdaman (2018) Yoewono (2018)
Ohlson	Imelda and Alodia (2017) Syamni et al. (2018)	Puro et al. (2019)	Mohd Johari et al. (2019)
Grigaravičius	Butkus et al. (2014)		
Bankruptcy prediction model based on artificial intelligence			
Decision tree	Gepp et al. (2010) Krušinskas et al. (2014)		

Analysis evidenced, that Altman model can be a significant tool in bankruptcy prediction. Three of the analyzed articles stated that Altman model is the most accurate, and 10 others agreed that it is suitable. Similar results of high accuracy were demonstrated by Springate, Grover, Zmijewski, Ohlson models. Other models are used quite rarely; however, some authors agree that they are also applicable. In summary, there is no unanimous opinion concerning the most accurate bankruptcy prediction model. When assessing the accuracy of separate models and their groups, differences may arise due to differences in the calculation methodology, the indicators used in the models and their quantity, as well as the significance given to the specific indicators. On the other hand, the different accuracy of the same model found in separate studies may be due to differences in the sample of data examined, i.e., the accuracy of the models may be affected by country, stage of the economic cycle, business sector, etc. Analysis of the scientific literature also evidenced, that there is a great lack of such research in the case of Lithuanian companies, especially when it comes to the application of the artificial intelligence models and comparison of the results not only among models within one group but also among different groups. Taking this into account, the *object* of this study is bankruptcy prediction models, and the *goal* is to perform the analysis of the accuracy of bankruptcy prediction models on the example of Lithuanian bankrupt companies.

Methodology

The research was carried out by using the financial statements, such as balance sheets, income statements, and cash flow statements of 23 bankrupt unlisted Lithuanian companies, which were selected using random sampling method. Selected companies went bankrupt during the growth phase of the economic cycle (2013-2019). There was no possibility to test the results using data of operating (financially healthy) companies due to the lack of the accessibility to the financial statements of unlisted companies. The research was performed employing 9 bankruptcy prediction models, that were selected on the ground of citation frequency. Eight of the models can be described as *classic statistical models,* and another one as *artificial intelligence model.* Using these models, the specific scores were calculated basing on which the probability of bankruptcy of each company was estimated. We used the same formulas as Prabowo (2019), Budrikienė and Paliulytė (2012), Puro et al. (2019), Grigaravičius (2003), and Mackevičius and Silvanavičiūtė (2006).

The classic statistical models can be divided into two groups based on the way the model was made. The group of linear discriminant analysis models includes such models as Altman, modified Altman, Springate, Taffler and Tishaw and Grover. Here, scores were calculated, and companies were grouped into three categories: supposed to go bankrupt (B), being in the grey area (G), and financially healthy (H) (see Table 2).

Table 2. Formulas and Interpretation of Scores for Bankruptcy Prediction Models Based on Discriminant Analysis

Model	Formula	Score
Altman	$Z=1.2X_1+1.4X_2+3.3X_3+0.6X_4+1.0X_5$ X_1=working capital/total assets; X_2=retained earnings/total assets; X_3=ebit/total assets; X_4=equity/total liabilities; X_5=sales/total assets	B: <1.81 G: 1.81–2.99 H: >2.99
Modified Altman	$Z=6.56X_1+3.26X_2+6.72X_3+1.05X_4$ X_1=working capital/total assets; X_2= retained earnings/total assets; X_3= ebit/total assets; X_4= equity/total liabilities	B: <1.10 G: 1.10–2.60 H: >2.60
Springate	$Z=1.03X_1+3.07X_2+0.66X_3+0.4X_4$ X_1=working capital/total assets; X_2= ebit/total assets; X_3=earnings before taxes/current liabilities; X_4=sales/total assets	B: <0.862 H: >0.862
Taffler and Tishaw	$Z=0.53X_1+0.13X_2+0.18X_3+0.16X_4$ X_1=earnings before taxes/current liabilities X_2=current assets/liabilities; X_3=current liabilities/total assets; X_4= (current assets-current liabilities)/operating costs	B: <0.2 G: 0.2–0.3 H: >0.3
Grover	$Z=1.650X_1+3.404X_2-0.016ROA+0.057$ X_1= working capital/total assets; X_2= ebit/total assets	B: <-0.02 G: -0.02–0.01 H: >0.01

It should be noted, that the Springate model is the only which does not have the "grey area" and allocate companies only to the groups of supposedly bankrupt and financially healthy companies.

The group of logistic regression models includes Zmijewski, Ohlson and Grigaravičius models (see Table 3). Here, the scores were calculated based on the formulas in the Table 3 at first, and then bankruptcy probability was calculated using the following formula:

$$P=1/(1+e^{-z}) \tag{1}$$

where P=probability of bankruptcy
z=score of each bankruptcy prediction model

Table 3. Formulas and Interpretation of Scores for Bankruptcy Prediction Models Based on Logistic Regression

Model	Formula	Score
Zmijewski	$Z=-4.3-4.5ROA+5.7X_2-0.004X_3$ X_2= total liabilities/total assets; X_3=current assets/current liabilities	B: P>0.6 G: 0.3<P<0.6 H: P<0.3
Ohlson	$Z=-1.32-0.407\log X_1+6.03X_2-1.43X_3+0.0757X_4-1.72X_5-2.37X_6-1.83X_7+0.285X_8-0.521X_9$ X_1=total assets/GDP index; X_2= Total liabilities/total assets; X_3=working capital/total assets; X_4=current liabilities/current assets; X_5=1, if total liabilities>total assets, if not – 0; X_6=net profit/total assets; X_7=cash flow/total liabilities; X_8=1 if net profit is negative, if not – 0; X_9= (net profit-net profit (n-1))/(net profit + net profit (n-1))	B: P>0.6 G: 0.3<P<0.6 H: P<0.3
Grigaravičius	$Z=-0.762+0.003X_1-0.424X_2+0.06X_3+0.22X_4-0.744X_5-0.189X_6+6.842X_7-12.262X_8-5.257X_9$ X_1=current assets/current liabilities; X_2=working capital/total assets; X_3=total assets/equity; X_4=total liabilities/equity; X_5=ebit/total assets; X_6=operating profit/sales; X_7=net profit/total assets; X_8=sales/working capital; X_9=sales/total assets	B: P>0.6 G: 0.3<P<0.6 H: P<0.3

The interpretation of scores for the logistic regression bankruptcy prediction models are the same as for the discriminant analysis models.

When applying the *decision tree* model, we used four different financial indicators to predict bankruptcy (see Table 4). Each was ratio was evaluated using the scores calculated in every step. After calculating the score of retained earnings to total assets ratio, a company was assigned to the group of "bankrupt" or "non bankrupt" companies. If a company was considered as bankrupt, next ratio was calculated, if not – its' financial information was no longer used in the further analysis and a company was treated as healthy. The same principle was applied to other ratios in this model.

Table 4. Ratios and Interpretation of Scores for Decision Tree Bankruptcy Prediction Model

Ratio	Score
Retained earnings to total assets ratio	If >0.15 – non bankrupt If <0.15 – bankrupt
Working capital to total assets ratio	If>0.33 – non bankrupt If <0.33 – bankrupt
Current assets to current liabilities ratio	If >1.1 – non bankrupt If<1.1 – bankrupt
Cash flow to total liabilities ratio	If>0.11 – non bankrupt If<0.11 – bankrupt

Using all the bankruptcy prediction models mentioned above, we performed our research in four stages:
1. Four years prior to bankruptcy.
2. Three years prior to bankruptcy.
3. Two years prior to bankruptcy.
4. One year prior to bankruptcy.

Four-year testing period was chosen because of the availability of data, as well as for the purpose of determining the pre-bankruptcy period during which bankruptcy prediction models demonstrate the most accurate results. In each stage we calculated scores for each company using the financial statements of the corresponding year prior to bankruptcy and then identified the probability of bankruptcy of the certain company. The accuracy of the bankruptcy prediction models was evaluated and compared according to percentage of companies attributed to the group of supposed bankrupts.

Results of the Analysis of the Accuracy of Bankruptcy Prediction Models

First, the results will be discussed in each group of the models analyzed according to the number of years prior to bankruptcy and afterwards the overall results will be compared and concluded.

Models based on discriminant analysis. The research evidenced, that the results of models, based on discriminant analysis were rather diverse *four years prior to bankruptcy*. Nevertheless, there is a main tendency that most of the companies four years before real insolvency were treated as healthy and with potential to operate successfully. The business continuity was forecasted for 70% of the companies by Grover model (other models treated lower number of companies as healthy) (see Figure 1). Springate model suggested, that 35% of the companies should have gone bankrupt even four years before actual bankruptcy. The same results were given by Altman, modified Altman and Grover models which predicted that 30% of the companies should have gone bankrupt four years prior to bankruptcy. Even though Springate model forecasted the biggest number of companies as supposed to go bankrupt, modified Altman model also evidenced a high accuracy – it predicted that only 39% of the companies are healthy, while Springate model attributed 65% of companies to this group. It should be noted that modified Altman model treated the high number (30%) of companies as situated in the grey area. Even though number of companies in red area according to this model is not the most (less if compared to Springate model), it founds a lower percentage of healthy companies, thus should be treated as accurate.

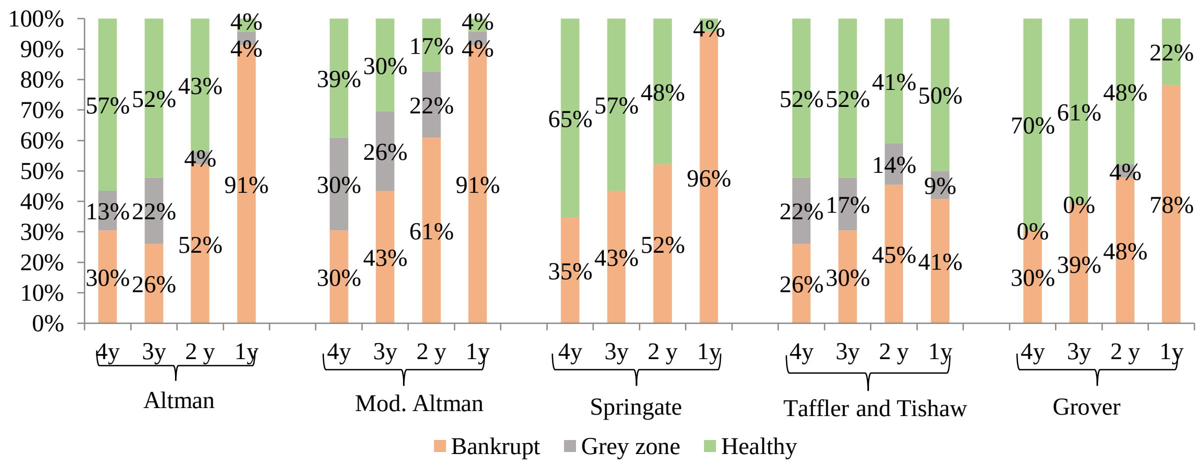

Figure 1. Results of the Scores Analysis for Models Based on Discriminant Analysis

(Source: compiled by the author)

Three years prior to bankruptcy, more companies were considered as possibly insolvent. Nevertheless, Grover model still treated that 61% of the companies are healthy. Similar results were given by Springate, Taffler and Tishaw, and Altman models – respectively, 57, 52 and 52% of companies were considered as healthy. Therefore, it can be stated that three years prior to bankruptcy, most of the models considered more than half of the companies as healthy. Different results were presented by modified Altman model – only 30% of companies were treated as healthy, moreover, scores of modified Altman, as well as Springate models indicated that 43% of the companies should go bankrupt. Besides that, it should be mentioned that modified Altman model again attributes more companies to the grey area if compared to other models. Three years prior to bankruptcy, 26% of the companies are considered being in the grey area by modified Altman model, while Altman model predicted the 22% have some financial difficulties. Taffler and Tishaw model predicted that 17% of the companies have potential problems, while Springate and Grover model did not assign any companies to this group.

After calculating the scores of models *two years prior to bankruptcy*, it was found that previously mentioned tendency of increasing percentage of scores that indicate bankruptcy are rising continuously. The least accurate predictions two years prior to bankruptcy were made by Springate and Grover models which forecasted that even 48% of the companies are healthy. Springate model forecasted that more than a half of the companies should go bankrupt (52%), while Grover model – 48%. Taffler and Tishaw model predicted that 41% of the companies are healthy, but 14% are in the grey area (have potential financial problems). The least number of financially healthy companies was forecasted by modified Altman model (only 17%). According to this model, 22% of companies were treated as having financial difficulties (grey area), and 61% – as potentially bankrupt. That is the highest score and thus accuracy among all the bankruptcy prediction models based on discriminant analysis two years prior to bankruptcy.

The results of the bankruptcy prediction *one year prior to actual insolvency* are dramatically different: most of the models based on the discriminant analysis forecasted bankruptcy with accuracy of more than 90%. Nevertheless, two models were an exception – Grover model forecasted that 78% of the companies are supposed to go bankrupt, and Taffler and Tishaw model was only 41% accurate in insolvency prediction.

In summary it can be stated that models based on discriminant analysis gave fairly accurate results in bankruptcy prediction. Though four years prior to bankruptcy all the models predicted with accuracy of only about 30%, two years before bankruptcy the scores changed, and forecast was with accuracy of about 50%. The Springate and Grover models should be mentioned separately as the first gave the most accurate and the second one – the least accurate bankruptcy prediction results four years prior to bankruptcy. Moreover, modified Altman model through all four years of analysis treated the least number of companies as healthy (a lot of them were assigned to grey area). The least accurate model one year prior to bankruptcy was the Taffler and Tishaw model and the accuracy of other models (except that of Grover) was more than 90%.

The results of our research are consistent with the results of other studies. Mackevičius and Silvanavičiūtė (2006) also proposed that Springate and Altman models demonstrate the highest accuracy; Altman model was treated as the most accurate also by Yoewono (2018), Mohd Johari et al. (2019). It also should be mentioned that many other authors treated these two models if not as the most accurate, then at least suitable for bankruptcy prediction. Our research also confirmed the results of Kanapickienė and Marcinkevičius (2014) and Krušinskas et al. (2014) who found that the least accurate model is that of Taffler and Tishaw. However, our results are contradictory to those of Kanapickienė and Marcinkevičius (2014) and Imelda and Alodia (2017) who found Altman model as the least accurate.

Models based on logistic regression. After calculating the scores of Zmijewski, Ohlson, and Grigaravičius models, it was found that all these models gave rather different results *four years prior to bankruptcy*. Zmijewski model predicted that 35% of the companies are healthy, while 17% have some potential financial problems (are in the grey area), and 48% were supposed to go bankrupt (see Figure 2).

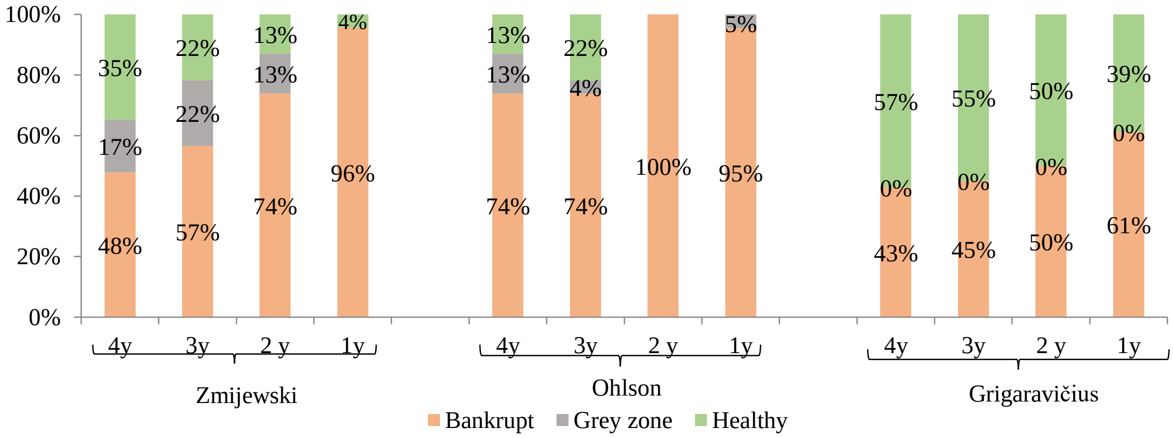

Figure 2. Results of the Scores Analysis for Models Based on Logistic Regression

(Source: compiled by the author)

The results of the Grigaravičius model were similar to those of Zmijewski model – 57% of the companies were treated as healthy, while 43% – as insolvent. Completely different results were given by Ohlson model: only 13% of the companies were treated as healthy, the same 13% of companies were treated as being in the grey area, and 74% – as potentially bankrupt. Therefore, it must be stated that Ohlson model is the most accurate among analyzed models in this group and even if compared with models based on discriminant analysis four years prior to actual bankruptcy. Zmijewski and Grigaravičius models were also more accurate than majority of the models in previously analyzed group at the same period.

Three years prior to bankruptcy, the Zmijewski, Ohlson and Grigaravičius models demonstrated even higher accuracy. Grigaravičius model gave almost the same results as the year before – the bankruptcy prediction is only slightly more accurate (45% of the companies were named as insolvent, while four years prior to bankruptcy it was 43%.). Zmijewski model predicted that 57% of the companies are supposed to go bankrupt, 22% are in the grey area and 22% are healthy. Ohlson model three years prior to bankruptcy gave the same results as four years prior to bankruptcy concerning potentially bankrupt companies (74%), however the number of companies treated as healthy increased (22%) and companies in the grey area decreased (to 4%). Nevertheless, it can be stated that the Ohlson model gave the most accurate results and tendencies of other models are in the right direction – the accuracy is growing closer to the year of actual insolvency.

The results of the analysis evidenced that *two years before actual insolvency* Grigaravičius model predicted bankruptcy for only half of the companies, while others were supposed to be healthy. Zmijewski model forecasted bankruptcy with 74% of accuracy. Model also treated 13% of the companies as being in the grey area and 13% as being healthy. Ohlson model forecasted with accuracy of 100% – it means that all the companies were supposed to go bankrupt, if based on the calculated probability.

Most of the models in this group were also the most accurate *one year prior to bankruptcy*. Zmijewski model predicted that 96% of the companies were supposed to go bankrupt. However, the accuracy of the Ohlson model (100% a year before) decreased and only 95% of the companies were treated as supposedly bankrupt. Again, the least accurate model was that of Grigaravičius (only 61% accuracy).

In summary, it can be stated that accuracy of the bankruptcy prediction models based on logistic regression was growing closer to actual insolvency. Moreover, even though Grigaravičius model includes more financial indicators than other models, this does not make it more accurate. Other two models gave better results, and the most accurate was that of Ohlson. According to our research results, models based on logistic regression are overall more accurate than models based on discriminant analysis.

The results of our research are consistent to those of Imelda and Alodia (2017), Syamni et al. (2018), who also named Ohlson method as the most accurate, and Puro et al. (2019) who treated it as appropriate for bankruptcy prediction. However, our results are contradictory to those of Mohd Johari et al. (2019) who found that Ohlson model demonstrates the lowest accuracy. Some authors also named Zmijewski method as accurate, the same as we can state according to our research results. It should be also mentioned that our results are contradictory to findings of Butkus et al. (2014), who unlike us found that the Grigaravičius model is highly accurate.

The decision tree model. The results of decision tree model evidenced that four years prior to bankruptcy, first stage indicator (retained earnings to total assets ratio) predicted bankruptcy for 70% of companies (see Figure 3). Closer to actual bankruptcy, the accuracy grew and one year prior to bankruptcy, this ratio predicted that all the companies should be insolvent. Working capital to total assets ratio was also the most accurate one year prior to bankruptcy when 91% of companies were supposed to be bankrupt. The lowest accuracy was observed two years prior to actual insolvency (70%). The current assets to current liabilities ratio demonstrated the lowest accuracy through the first three analyzed years (39 to 48%), however one year prior to bankruptcy, the number of supposedly bankrupt companies according to this ratio increased to 87%. The last stage indicator, cash flow to total liabilities ratio predicted that majority of the companies should have gone bankrupt even four years prior to bankruptcy (96%), the same accuracy was observed two years prior to bankruptcy. Moreover, three and one year prior to bankruptcy, the accuracy of this ratio was 100%.

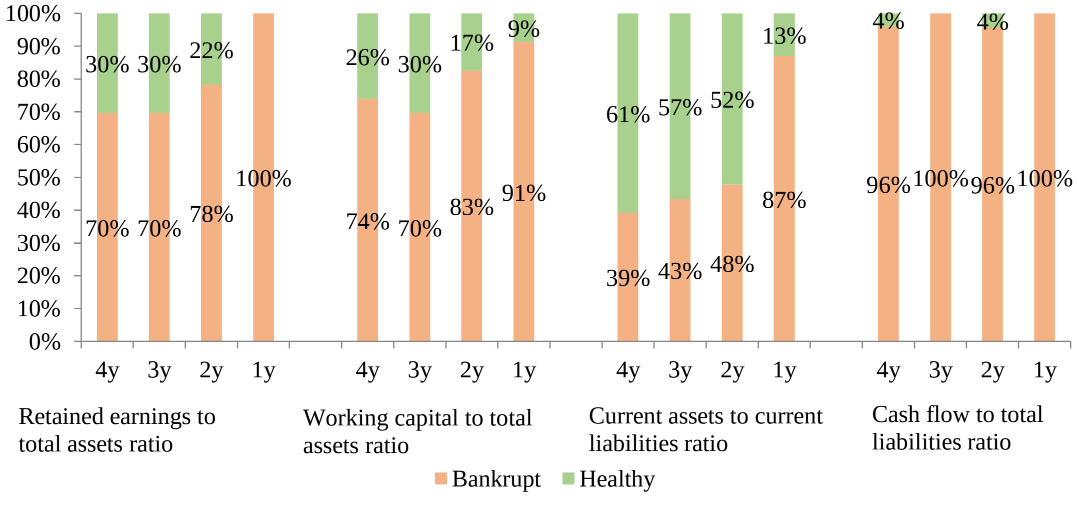

Figure 3. Results of the Indicators Analysis for the Decision Tree Model

(Source: compiled by the author)

In summary, it can be stated that accuracy of the decision tree model (the only bankruptcy prediction model based on artificial intelligence we analyzed in this research) was higher if compared to other models but demonstrated the same tendency of increased accuracy in the last year.

The results of our research are consistent with those of Gepp et al. (2010), who also named the decision tree as the most accurate bankruptcy prediction model.

Comparison of the results. The results of this study evidenced that bankruptcy prediction models help to forecast insolvency of a company more than one year prior to bankruptcy. That means, there is a possibility for companies to take actions at the right time to save their business when the problems are not too deep and far-gone. However not all models are equally accurate (see Figure 4).

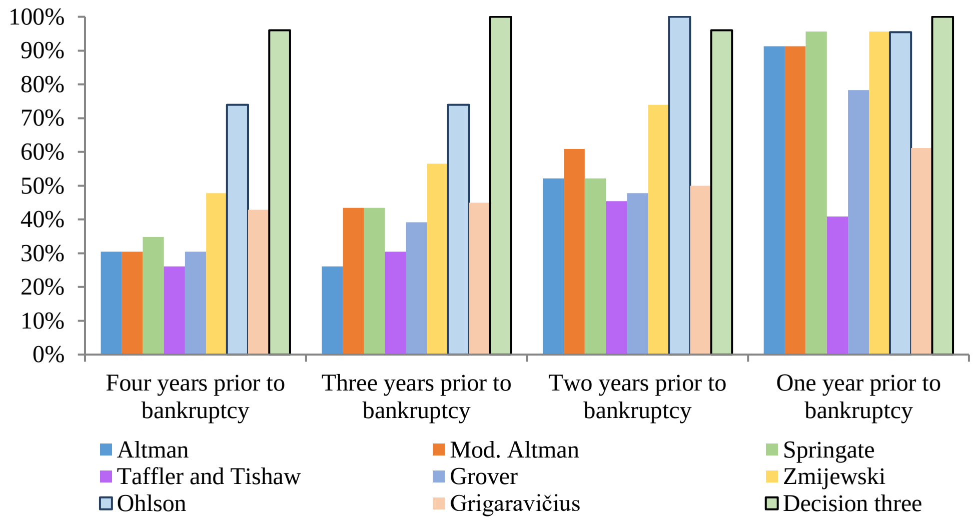

Figure 4. The Accuracy of the Bankruptcy Prediction Models

(Source: compiled by the author)

Comparison of the results of bankruptcy prediction models based on discriminant analysis and logistic regression allows to state that the most accurate results one year prior to bankruptcy were given by Ohlson model. As it can be seen in the Figure 4, Zmijewski (orange) and Ohlson (blue) models are quite accurate even earlier than one year prior to bankruptcy (four years prior to bankruptcy accuracy of Ohlson model was 74%). Later, three, two and one year prior to bankruptcy, the accuracy of Ohlson model was growing and two years before bankruptcy it predicted with 100% accuracy. Therefore, it can be stated, that Ohlson model is significantly more accurate than all discriminant analysis models, as well as other logistic regression models. It also should be mentioned that there is no direct dependence on the number of financial indicators used in the model and its accuracy: Grigaravičius model which uses the biggest number of indicators was one of the least accurate models in the group of logistic regression models and one of the least accurate overall. The exceptional results were demonstrated by the decision tree model. This bankruptcy prediction model forecasted with 100% accuracy almost every year out of four before the actual insolvency and demonstrated the highest accuracy out of all bankruptcy prediction models that were analyzed.

Comparison of the results of all analyzed bankruptcy prediction models evidenced that the decision tree model, as well as the Ohlson and Zmijewski models demonstrated the highest accuracy and the question here arises why the results of none of the bankruptcy prediction models that were based on discriminant analysis were as high as the results of logistic regression or decision tree models. The first reason could be that discriminant analysis-based models use lower number of financial indicators (as compared to the logistic regression-based models). Although the number of financial indicators does not automatically mean that the forecast will be the most accurate (the case of the Grigaravičius model), the variety of ratios seem to be one of the success elements in the Ohlson model. The second reason could be that discriminant analysis-based models, contrary to the logistic regression-based models, emphasize the short-term solvency indicators and profitability before taxes and financing effect. The Altman models, which assessed total solvency together with short-term solvency indicators, predicted bankruptcy with higher accuracy if compared to other models in this group. Third, none of the discriminant analysis-based models use any ratios that would be related to information other than from the financial statements. Meanwhile the Ohlson model uses a GDP index. This model also requires using cash flows in the calculation of bankruptcy prediction, as well as the decision tree does. Nevertheless, not all models, even the most accurate ones, demonstrated the same results for all companies. This means that the prediction may be the most accurate when several models are used; based on the results of our research, the best way to predict bankruptcy in time is to use the decision tree, Ohlson and Zmijewski models.

Our research results are consistent to the results of Gepp et al. (2010), Imelda and Alodia (2017), Syamni et al. (2018), Gunawan et al. (2017), Husein and Pambekti (2014) who also found that the models based on artificial intelligence and logistic regression are the most accurate and therefore the best suitable to bankruptcy prediction.

Summary and Discussion

Bankruptcy can cause unwanted damages not only to the bankrupt companies, its owners, employees, other related parties, but to all members of the society as well. Timely bankruptcy proceedings can reduce the damages to all the interested parties of the business. Therefore, it is important to detect early signs of potential insolvency, forecast the future of the company and act on it. Potential financial problems in companies may be identified using bankruptcy prediction models. However, there are many of bankruptcy prediction models, they use different number of indicators and apply different calculation methods, according to which are divided into separate groups. For this reason, it is purposeful to compare the accuracy of individual bankruptcy prediction models and their groups.

The discriminant analysis-based models predicted with accuracy of only about 30% four years prior to bankruptcy however the accuracy increased by the actual bankruptcy time. The Springate model gave the most accurate and the Grover model gave the least accurate prediction results four years prior to actual bankruptcy. The least accurate model one year prior to bankruptcy was that of Taffler and Tishaw (41%); the accuracy of other models was more than 90%, except the Grover model (78%). The standout in this group is the modified Altman model which treated the least number of companies as healthy through all four years of analysis.

The accuracy of logistic regression-based bankruptcy prediction models was also growing closer to actual bankruptcy. The highest accuracy in this group was demonstrated by the Ohlson model (74% four and three years to bankruptcy, 100% two years prior to bankruptcy and 95% one year prior to bankruptcy). It should be also mentioned that the Grigaravičius model includes the biggest number of financial indicators however this model was the least accurate in this group (43-61%).

The accuracy of the decision tree model (the only artificial intelligence-based bankruptcy prediction model, which can be described as the most innovative however the least explored model of all used in this research) also increased in the last year however, considering separate ratios was not lower than 70% during all the analysis period (except current assets to current liabilities ratio).

The results of the research of bankrupt companies in Lithuania evidenced that the most accurate models and therefore the most suitable for bankruptcy prediction are the decision tree as well as the logistic regression-based models of Zmijewski and Ohlson. The least accurate were the discriminant analysis-based model of Taffler and Tishaw as well as the logistic regression-based model of Grigaravičius that evidenced the accuracy of only 60% or less oven one year prior to actual bankruptcy.

As our research encompass financial statements of only 23 companies that went bankrupt in one phase of the economic cycle (20132019), the data was insufficient to verify if the models are equally accurate under different situations and conditions. A larger number of companies would increase the reliability of the results and would allow to estimate if the accuracy of models change as regards to company size, funding structure, business sector, phase of the economic cycle and other internal as well as external factors. Moreover, the research could be extended including data of non-bankrupt companies, which would allow a more reliable assessment of the accuracy of bankruptcy models by examining if bankruptcy is not predicted for financially healthy companies.

Even though this research has limitations because of data insufficiency, it proves that application of bankruptcy prediction models is important and even essential matter in everyday business activity. Considering today's economic situation, it is exceptionally crucial to observe the financial condition of a company, and bankruptcy prediction models (specifically, the decision tree, Ohlson and Zmijewski models or their combination) are a relevant, suitable and uncomplicated way to fulfill this requirement.

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Contact person:

Jurgita Stankevičienė, Kaunas University of Technology; Gedimino street 50, LT-44029, Kaunas, Lithuania; e-mail: jurgita.stankeviciene@ktu.lt