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Business Management and Methods of Predictive Financial Analysis of Companies' Activity

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Abstract

The prediction of the future situation of an enterprise can be made by means of one-dimensional and multidimensional discriminant analysis methods. Generally, these discriminant analyses use the financial ratios methods. The prediction of the future situation of an enterprise can be made by means of one-dimensional and multidimensional discriminant analysis methods. Generally, these discriminant analyses use the financial ratios methods. The article aims to apply one-dimensional discriminant analysis in specific conditions of economic practice. The empirical part of the research proves that this method can better warn against nearing bankruptcy by predicting whether a business will or will not be sustainable. The analysis of multiple scientific works has established that the reliability of one-dimensional discriminant analysis methods can differ from multidimensional discriminant analysis methods. The research conducted verified the above in a group consisting of prosperous and non-prosperous business entities. The research was conducted based on the sample of enterprises surveyed and showed that one-dimensional discriminatory methods had higher reliability than multidimensional ones. The research does not guarantee that a 100% reliable method will be found; however, it provides for the use of a combination of multiple methods and the assumptions on which these existing methods work.

Keywords: financial indicator, one-dimensional discriminant analysis, sustainable business.

JEL: M21, L20

Introduction

Maximizing profit or maximizing the market value of an enterprise was considered to be the main business objective until recently. Today, profit is considered to be a partial business objective, yet its importance cannot be denied. Although profit, even in the meaning of the valid legislation of the Slovak Republic (one of the five basic characteristics

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of business), produces the main result of entrepreneurial activity. Its creation must also take into account the current stakeholders and the future generations, who must not be threatened while meeting their needs (Mura, 2018). Taking these factors into account, one can arrive at the creation of a business sustainability concept, where corporate social responsibility (CSR) is gaining legitimacy (Gao et al., 2015; Svec et al., 2017). Kunz (2012) states that the concept of the CSR is not developed at a sufficient level in Eastern and Central Europe, but when compared with the countries of Western Europe, they have shown a faster growth trend.

In the long term, the accounting indicators of profitability show significant differences between socially responsible and conventional firms (Lassala et al., 2017). These are early warning systems, which are likely to predict financial difficulties before they occur (Zieba et al., 2016; Tian et al., 2015). Kuhn (2013) proved that even though the examined files are robust in size, it is very easy to work with them and verify the established research hypotheses. The credit risk of investing is responsible for the investor increasing the likelihood of market failure (Charitou et al., 2004). The question of whether a business is sustainable is particularly relevant for stakeholders who are somewhat dependent on a business but do not always have the competence to make decisions (Zhao et al., 2018). Creditors are wondering if their receivables will be settled, banks are making analyses to decide whether they can extend a credit, minority shareholders are interested in dividend payments and growth of share market value. These stakeholders may not have real managing authority, so early warning systems are important for them in order to make decisions before complications arise.

Sustainability entrepreneurship is directly related to the financial situation of the enterprise (Liu et al., 2019). The enterprise with positive financial balance has a bigger chance to stay in the market than an enterprise experiencing financial problems. In the next place, as far as the enterprise prefers CSR principles, the stakeholders are more likely to stay loyal to it, which will subsequently affect its financial health (Agarwal et al., 2008; Hasan, 2017). Therefore, it is very important to be concerned with the prediction of a future situation in the enterprise (Gan et al., 2018). In this case, it is possible to compare the financial situation of the enterprise with the tip of an iceberg. Some data about the enterprise can be easily obtained because they are publicly available in the Slovak Republic.

Lukason (2014) argues that one should know the extent, reliability, and probability of efficient business functioning. Corporate strategy must necessarily be the bearer of corporate social responsibility (Ofori et al., 2014; Nastišin, 2016). The answers to these research questions vary widely by different researchers. The factors that significantly affect the company management are slightly reflected in the company's financial indicators. The company must also cope with accidental phenomena, such as a lawsuit or natural disasters. The predictability of such phenomena is very low or impossible. However, this does not mean one should ignore business sustainability. These methods still have some predictive ability, which cannot estimate all potential problems but at least the most relevant ones. The authors of this article also approach the testing of the ability to discriminate these methods.

Predictive financial analysis primarily serves to forecast the development of the financial situation of a business entity. Abellán et al. (2014) emphasize that the company's financial situation and social trend of its performance follow the same trend (Skalická et al., 2019; Gospodarchuk et al., 2019; Okanazu et al., 2018). R. Bender (2014), R. A. Brealey, S. C. Myers and A. J. Marcus (2012), E. I. Altman, G. Sabato and N. Wilson (2010), B. Swiderski, J. Kurek and S. Osowski (2012) were the best-known authors who tried to avoid financial strain through verifying the discriminating ability of indicators. They succeeded in reducing numerous indicators to those indicators that have "good discriminating ability" and predict a financial collapse. The essence follows from a comparison of the results by individual solvent (prosperous) and insolvent (non-prosperous) enterprises.

Relevant sources of information to predict the financial condition of an enterprise include the following: data and subsequent analysis of current and future cash flows; financial statements and their analysis; information from the external environment, such as data on market prices of shares and the overall situation in the financial market (Wang et al., 2014; Salman, 2011). Korol (2013) considers the forecast of a company's financial situation as a particular system of early warning and does not provide any guidance on how the company's financial situation can be improved. Chen and Du (2009) argue that the values of financial indicators of companies are changing in parallel with the radical changes in the global economic environment. Quiry (2014) advocates that objective rational decision making is unrealistic because it places excessive demands on the cognitive abilities of the decision maker. Cho et al. (2009) demonstrate that even a slight improvement in credit risk assessment helps to reduce the costs associated with non-performing loans. These models help managers monitor the entity's performance in a particular time horizon and identify important trends. Abellán and Mantás (2014) emphasize that creating a reliable credit score model brings several benefits in terms of reducing the cost of credit analysis.

Thus, the purpose of this research paper is the application and examination of the one-dimensional discriminant analysis in specific conditions of economic practice.

Materials and Methods

During predictive financial analysis, it is necessary to take into account the sector in which an enterprise operates. The discriminating ability of the indicators states how an indicator can predict the future financial situation of an enterprise. If it shows different values for prosperous and non-prosperous enterprises, then it pertains to good discriminating ability.

The normal distribution is the distribution that governs our research population. By the end of the 1960s, one-dimensional statistical methods were used. Beaver examined the one-dimensional financial analysis indicators on a sample of 69 prosperous and 69 non-prosperous enterprises (Beaver, 1966). The financial indicators that are most sensitive in order to be able to recognize the financial situation of the examined entity include cash flow into liabilities, net profit into total assets, liabilities into total assets, working capital into total assets, urgent assets into short-term liabilities.

The multidimensional discriminant analysis considers precisely given indicators for assessing the future development of classified enterprises. These indicators are assigned significance weights, and their discriminating ability has been verified in various types of market economies. The following methods of multidimensional discriminant analysis were used in the article: the modified Altman Z-score for the Czech Republic, The Creditworthiness Index, The Springate model, The Taffler model, and Index IN 05. Multidimensional methods of discriminant analysis take into account several indicators that should be independent of each other, contributing to a comprehensive assessment of the future prosperity of an enterprise.

In general, it is assumed that due to the complexity of multidimensional discriminant analysis methods and their view on enterprise health from multiple perspectives, they should achieve better discriminating ability than one-dimensional discriminant analysis methods. However, considering more complicated construction, it can be assumed that the application of multidimensional methods will often lead to errors as they are composed of several indicators. If only one of these indicators shows extreme values that can be caused by an unusual low denominator, it will subsequently affect the overall calculation and the resulting value of the model.

Hypotheses can be formulated based on these findings. It is not clear whether the discriminating ability will be better or worse based on the given reasons.

H1: One-dimensional discriminant analysis methods will display a different discriminating ability compared to multidimensional discriminant analysis methods.

H0: One-dimensional discriminant analysis methods will not display a different discriminating ability compared to multidimensional discriminant analysis methods.

A median test was used to verify the hypotheses. In the first step, a sample of enterprises was selected, including prosperous and non-prosperous enterprises. As a criterion of non-prosperity, the entry of the enterprise into bankruptcy and its subsequent going bankrupt was chosen. Enterprises that went bankrupt in 2013 and 2014 were examined from the sources available. Since insolvency proceedings are a process that may take several years, it was examined whether or not the undertakings had ceased their business activity at the date of the test or whether they were deleted from the Commercial Register. In 2013, 30 enterprises went bankrupt, and had subsequently gone out of business by the date of the test. In 2014, there were 22 businesses.

The number of prosperous and non-prosperous companies must be equal to conduct the median test. The data from non-prosperous companies were collected 1 to 4 years before their bankruptcy. The authors of this article assume that non-prosperous and prosperous companies will show different financial findings if the methods with a good discriminating ability are applied. Since enterprises are obliged to prepare financial statements within a year, the data interval is one year. It was necessary to find prosperous enterprises for these non-prosperous ones in order to use the median test. They were chosen based on the assumption that every non-prosperous business had a prosperous match from the same industry. In addition, it was also monitored for prosperous businesses whether their business activity continued to run and whether they had not gone out of business by the time of testing. For the summary of financial statements used for testing see Table 1.

Table 1. Number of financial statements used

Year of bankruptcy declaration	Total	Financial statements by period				
		2009	2010	2011	2012	2013
2013	148	38	40	34	36	-
2014	112	-	24	24	32	32

The results of individual indicators were compared, commented, and it was examined whether one-dimensional discriminant analysis methods had a different error rate than multidimensional analysis methods (MDA). The classification capability of the proposed prediction model was evaluated on the basis of four selected tools – Type I error, Type II error, Predictive accuracy, Sensitivity. The theoretical basis for the calculation of the values of the indicators of evaluation of the predictive ability of the neural network model is a contingency (Table 2.). The cells in the table indicate the percentage of true positives (TP), false positives (FP), false negatives (FN) and true negatives (TN).

Table 2. Confusion matrix

		Predictive value	
		Non – bankruptcy	Bankruptcy
Actual value	Non – bankruptcy	TP	FP
	Bankruptcy	FN	TN

From the values of the observed and actual results of the contingency table, we calculate the values of the tools for measuring the performance of the model:

Type I error:

$$Type\ I\ error = \frac{FN}{FN+TP}, \quad (1)$$

Type II error:

$$Type\ II\ error = \frac{FP}{TN+FP}, \quad (2)$$

Predictive accuracy:

$$predictive\ accuracy = \frac{TP+FN}{TP+TN+FP+FN}, \quad (3)$$

Sensitivity:

$$sensitivity = \frac{TP}{TP+FP}, \quad (4)$$

Results and Discussion

The selected indicators were tested using the median test. Consequently, a graphical comparison of the individual results achieved was performed separately for the group of prosperous and non-prosperous enterprises. Within each methodology, the median for the period of 1, 2, 3 and 4 years before bankruptcy was calculated. In the case of the good discriminating ability of the given method, Figure 1. shows different values of prosperous and non-prosperous enterprises.

Cash flow to total liabilities (CF/TL). Figure 1 demonstrates that the discriminating ability of the cash flow regarding the total liabilities method is quite good. This method clearly showed low values for non-prosperous enterprises and apparently high values for prosperous enterprises in all the observed periods, as shown in Figure 1. By comparing the median values within individual groups, it can be seen that prosperous enterprises are clearly distinguished from non-prosperous ones, which confirms the good discriminating ability of this indicator.

Net profit on total assets (NP/TA). The methodology based on net profit already shows deterioration in the discriminating ability, especially for a longer period before bankruptcy, as shown in Figure 1. When comparing the median values of individual groups of prosperous and non-prosperous businesses, we can see a relatively good discriminating ability that improves with approaching bankruptcy.

Total liabilities to total assets (TL/TA). In this case, this is the only indicator of all the tested ones, where the higher values are characteristic for non-prosperous enterprises and lower values for the prosperous ones. The interesting thing about this method was that in one case, the indebtedness reached a value of 2,538.1 for non-prosperous enterprises (this is a proportion, not a percentage). This was achieved in an enterprise that reported very small assets (just a tiny balance on the financial accounts) and extremely high liabilities (the enterprise's liabilities exceeded its assets and the value of the equity was negative). Good results were achieved in the comparison of the median values of each group in Figure 1, where the shorter the time to bankruptcy, the larger the span. In this case, it can be stated that the less indebted an enterprise is, the lower the probability of bankruptcy. The median value of indebtedness of the prosperous businesses ranged from 40 to 60%.

Working capital to total assets (Work C/TA). The indicator of the share of working capital in total assets can also be significantly influenced by the sector in which the enterprise operates. Other working capital values are reported by manufacturing or service enterprises as well as those involved in trade. However, in the case of the share of working capital in total assets, significant discriminating ability was seen. In some cases, there was an increase in the working capital of the monitored sample due to the fact that non-prosperous businesses were selling their long-term assets just before bankruptcy – probably due to the provision of liquid assets needed to cover current liabilities. This fact, however, did not significantly affect the results, and the method had a good discriminating ability, which is also confirmed in Figure 1.

Current assets on current liabilities (CA/CL). Similarly, to the previous indicator, the share of current assets on current liabilities depends on the business sector in which the enterprise operates in, as well as related to the enterprise's negotiating power. By comparing the median values of prosperous and non-prosperous businesses, we can see the relatively good discriminating ability of this indicator. With declining years to bankruptcy, the span between the measured median values of these groups increased, as shown in Figure 1. One-dimensional discriminant analysis methods have been relatively reliable in separating non-prosperous businesses from prosperous ones. However, multidimensional discriminant analysis methods showed poorer results of the sample examined. Its discriminating ability was weaker.

Altman Z-score for the Czech Republic (Altman CZ). Surprisingly, the Altman Z-score showed relatively high extreme values over some periods. If the enterprise had negative equity, it could have had relatively high Altman Z-score values. It is therefore important to note that Altman Z-score may show inappropriate values if the enterprise has a negative equity. In such a case, it may not be needed to carry out an "ex ante" financial analysis because the mere fact of negative equity denounces the lack of prosperity of the undertaking itself.

The comparison of the median values of Altman Z-score for the Czech Republic is based on good discriminating ability, as shown in Figure 1. Non-prosperous enterprises experience is continuing to negative development with the upcoming bankruptcy, while prosperous enterprises maintain a stable level.

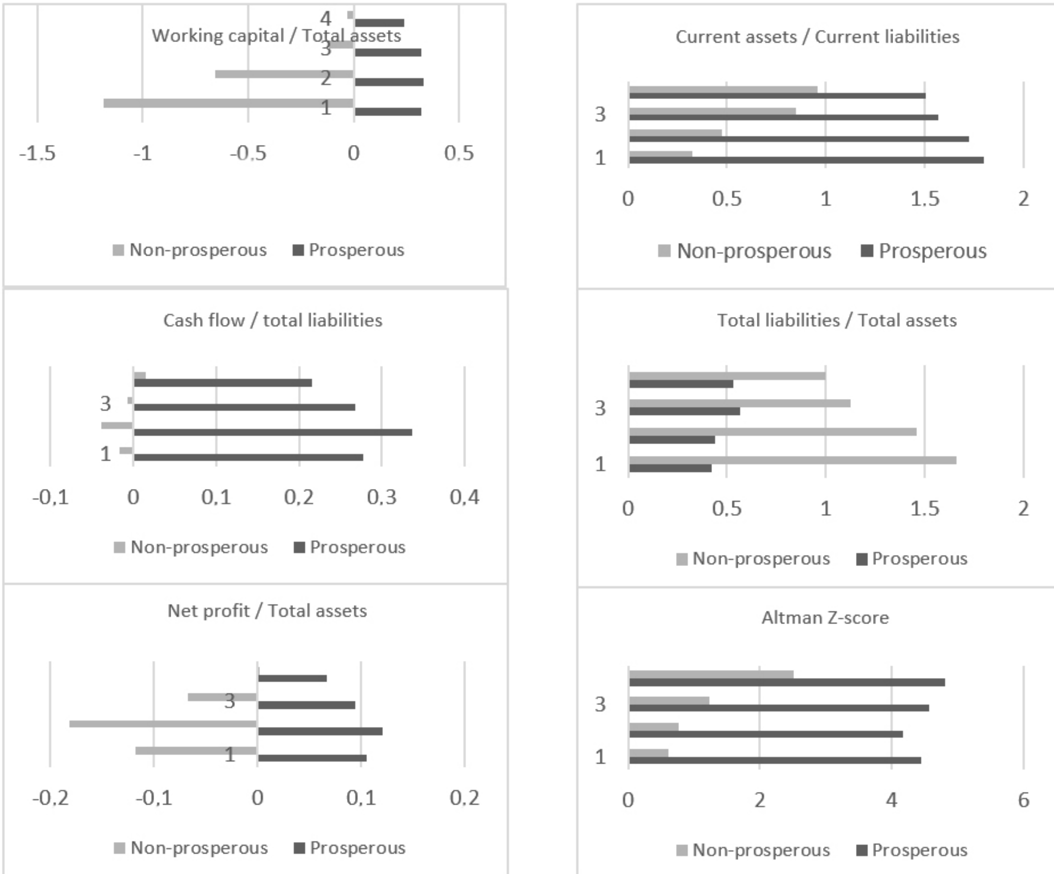

Figure 1. Results of classical prediction models I

Creditworthiness index. The Creditworthiness index operates with a share of net profit on total assets. When comparing the median values of prosperous and non-prosperous enterprises in Figure 2 they have a relatively good discriminating ability. It can therefore be said that this method is usable, but extreme cases have to be selected.

The Springate model. This is another method in which extreme values are reported, especially for non-prosperous enterprises. Up to three of the four indicators there is part of this method that have total assets in the denominator, which once again creates extremes for over indebted businesses and negatively affects the assessment of discriminating ability. Better results were achieved in the case of the comparison of median values, and the model was able to more or less clearly distinguish prosperous businesses from non-prosperous, as shown in Figure 2. Non-prosperous enterprises showed some improvement, but the span is still evident one year before bankruptcy.

The Taffler index. Similarly to all methods which use ratio indicators, the Taffler index also reached relatively high extreme values. These were again reflected in the non-prosperous enterprises, which showed relatively high positive values in three cases, which may lead to the erroneous inclusion of non-prosperous enterprises for the prosperous ones, as shown in Figure 2. The comparison of the median values showed a relatively stable span, which narrowed dramatically one year before bankruptcy, but this span was only decimal numbers for the whole of the monitored period.

IN 05. In terms of the IN 05 index, a large number of enterprises had to be excluded from testing, as the results often reported a logical error (division by zero). After reducing logical errors in the test sample, the IN 05 index achieved relatively good results, especially in the period of one and two years before bankruptcy, as shown in Figure 2. This is confirmed by the comparison of median values, where a relatively good discriminating ability of index IN 05 was acquired one or two years before bankruptcy. These values did not show any significant deviations for the period of four years before bankruptcy.

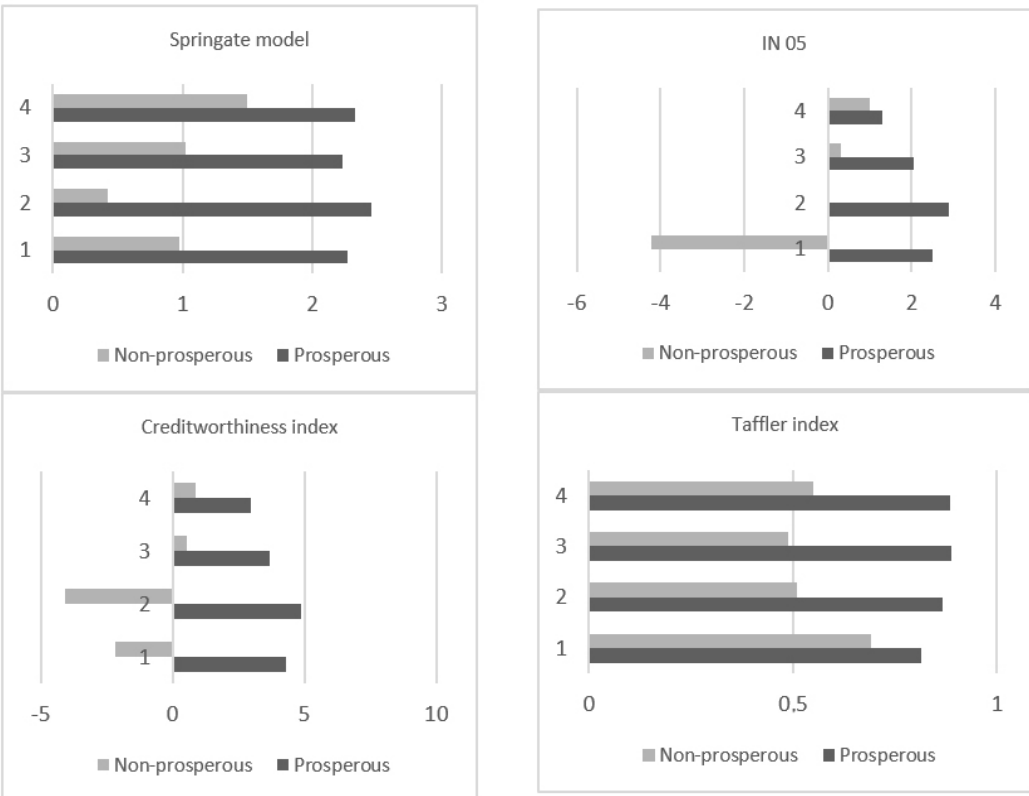

Figure 2. Results of classical prediction models

These findings can be summarized for individual indicators as follows: Table 3. quantifies the discriminating ability (DA) of indicators for each period. There are two numbers in the DA columns, the number before the slash shows the number of correctly ranked tested enterprises. In the area where the percentages are given, there are only correctly classified assessed companies. When this value is higher, the detection rate of failing processes is higher. The “Average” column shows the average percentage of the correct business rankings. These percentages were not counted separately for prosperous and non-prosperous businesses, since their values are equal (exactly the same percentage of prosperous businesses were correctly classified as non-prosperous).

Table 3. The results of the median test

Method	Average	1 year		2 years		3 years		4 years	
		DA	%	DA	%	DA	%	DA	%
CF/TL	80.19%	29 / 4	87.88%	26 / 6	81.25%	24 / 7	77.42%	23 / 8	74.19%
NP/TA	74.32%	26 / 7	78.79%	25 / 8	75.76%	24 / 8	75.00%	21 / 10	67.74%
TL/TA	83.61%	5 / 28	84.85%	30 / 3	90.91%	26 / 6	81.25%	24 / 7	77.42%
WorkC/TA	80.43%	29 / 4	87.88%	29 / 4	87.88%	24 / 8	75.00%	22 / 9	70.97%
CA/CL	82.55%	29 / 4	87.88%	28 / 4	87.50%	24 / 7	77.42%	24 / 7	77.42%
Altman CZ	77.18%	25 / 8	75.76%	25 / 7	78.13%	24 / 7	77.42%	24 / 7	77.42%
Creditw. index	67.80%	13 / 9	59.09%	17 / 5	77.27%	17 / 7	70.83%	16 / 9	64.00%
Springate model	75.59%	24 / 9	72.73%	26 / 6	81.25%	23 / 8	74.19%	23 / 8	74.19%
Taffler index	61.54%	18 / 15	54.55%	19 / 13	59.38%	19 / 12	61.29%	22 / 9	70.97%
IN 05	71.18%	8 / 4	66.67%	14 / 2	87.50%	12 / 4	75.00%	10 / 8	55.56%

The best results of the given sample had the ratio of total liabilities to total assets (up to 83.61%), followed by the share behind it are the ratio of current assets and the share of cash flows to total liabilities. In general, we can state that indicators that contain liabilities, show a relatively good discriminating ability.

Multidimensional Discrimination Analysis (MDA). We used the variables x_1=net profit to total assets, x_2=current assets to current liabilities, x_3=current liabilities to total assets, x_4=working capita to total assets, x_5=current assets to total assets. The resulting discriminatory function has the following form: D (f)=D (x_1, x_2, x_3, x_4, x_5). Since the multivariate discriminatory function possesses the properties of multivariate statistical analysis, it was advisable to perform multivariate tests of the predicative ability of individual ratios, which were selected as input variables of the model. We used multivariate tests of statistical analysis, namely Wilkś lambda and F-statistics. The quantified p value is shown in Table 4.

Table 4. MDA model results

Variable	p-value	Discriminatory correlation
Net profit to Total assets	0.008*	-0.553
Current assets to Current liabilities	0.000*	-0.71
Current liabilities to Total assets	0.013*	0.522
Working capita to Total assets	0.080	-0.471
Current assets to Total assets	0.621	-0.201

From this table it is clear that the x_1=net profit to total assets, x_2=current assets to current liabilities, x_3=current liabilities to total assets are best able to highlight the differences between healthy and failing enterprises in a one-dimensional analysis. Indicator Values (p-values) Working capital/total assets and Current assets/total assets indicate that, on their own, these indicators are not able to statistically significantly differentiate the differences between a healthy business and a failing business. The canonical discriminatory function within our sample can distinguish well between two heterogeneous groups of companies. The overall performance of the MDA model is listed in Table 5.

Table 5. Prediction

Index	File
Type I error	49.48 %
Type II error	13.03 %
Accuracy of prediction	72.42 %

The MDA model was able to correctly classify 72.42% of enterprises on the test sample, a value that is also affected by the high values of the first (49.48%) and the second (13.03%) error rates. Financial ratios do not follow the normal distribution, there are also non-linear relations between dependent and independent variables, multicollinearity is present between variables and heteroscedasticity is complicated by the possibility of using model results.

To compare two groups of methods, the independent sample t- test was used. Methods of one-dimensional discriminant analysis more successfully distinguished between prosperous companies compared to those which went bankrupt. Prediction accuracy measured by percentages was higher M=80,22, SD=6,53 for methods of one-dimensional discriminant analysis, compared to methods of multi-dimensional discriminant analysis M=71,27, SD=9,49 and the difference was significant t(38)=3,48; p=0,001. So we accept the hypothesis H_1 and reject the hypothesis H_0. The difference between the reliability of one-dimensional discriminant analysis methods and the reliability of multidimensional discriminant analysis methods is statistically significant on the given enterprise sample.

Both one-dimensional and multidimensional discriminant analysis methods have their place in financial analysis. They should serve external users of financial statements who do not have managerial accounting data. Several authors try to find the right method to best and reliably summarize the chance of an enterprise to be prosperous or non-prosperous (Chung et al., 2013; Okanazu, 2019).

At this time, it is very difficult to make financial forecasts within the business activities of individual businesses. It is necessary to look for answers to questions such as how much money needs to be obtained, is it possible to realize the payment of the dividend, what price for acquisition is optimal (Bender, 2014). To sum up, despite all efforts, there will probably not be a method that would perfectly distinguish a prosperous business from a non-prosperous one. The opposite situation could be seen in the examined sample, and a prosperous enterprise seemed to be non-prosperous. This may be related to the construction of a particular model. If the economic result is used as one of the indicators, the financial situation may be distorted, as this result can often be reduced by the various tax optimization trends of the enterprise. The disadvantage of the financial statements is that they are available for an external user only once a year. Therefore, there should be a further effort to focus on indicators that fall into a one-dimensional discriminant analysis. This may include trying to use more synthetic indicators, where there is a low probability of zero value in some enterprises, thereby avoiding unnecessary logic errors.

Currently, there is room to model predictive bankruptcy models that would have both commercial and public use. In business practice and in the practice of financial institutions, simple models of financial analysis are used, or evaluations based on one-dimensional statistical analysis of financial data.

Another problem is the actual construction of ratio indicators. An enterprise had to be often excluded from the testing because the calculation contained a logical error (division by zero). This is the case when during the construction of an “ex ante” financial analysis indicator (regardless of whether one-dimensional or multidimensional) a ratio indicator is used, which may often show zero in the denominator. An example of this can be the cost of interest that is not reported by every enterprise. In general, the more analytical an item is (it is only a part of the corporate statements, e.g. short-term trade liabilities), the greater the chance of it being zero for some groups of enterprises, compared to more synthetic items (e.g. short-term liabilities, including those from trade and others).

From a practical point of view, several obstacles are associated with the use of the above-mentioned models. First of all, these models assume a normal distribution of the probability values of financial indicators, which according to many studies is not met. Another limitation is that the prediction models were used on samples of foreign companies.

Conclusion

A distinctive feature of selected discriminatory methods was tested on a sample of prosperous and non-prosperous enterprises. Based on the results, one-dimensional discriminant analysis methods have different discriminating ability than multidimensional discriminant analysis methods, which proves the full validity of hypothesis H1. With the implementation of a one-dimensional discriminatory analysis, there was clearly a larger number of financial statements as well that were also tested, as there were often no logical errors in the calculation since the indicator usually contained only one fraction.

It was also found on the sample of enterprises that none of the tested methods showed 100% reliability. The assessment of future developments requires none of the sub-indicators to show an extremely high or low value, which may distort the overall result. It is also necessary to examine whether an enterprise creates negative equity. In such a case, the enterprise can be considered directly as non-prosperous, so no further calculations need to be performed. According to the research carried out, it is more than necessary to draw attention to methods such as methods of discriminatory analysis to analyze the financial condition of companies in Slovakia. The research sample of the enterprises has shown that even these methods can better warn against nearing bankruptcy by predicting whether a business will or will not be sustainable. As a consequence, another research should consider the methods, which should be tested on a bigger sample of enterprises. On the other hand, the methods of multi-dimensional discriminant analysis can provide a more complex forecast of the financial situation in the enterprise; however, when many indicators are used, it may result in distorted conclusions, while some of the sub-indicators show extreme values. For this reason, the method of the multi-dimensional analysis, applied to the research sample of the Slovak enterprises, showed lower reliability in the prediction of sustainability entrepreneurship than the method of one-dimensional analysis.

If a company wants to reduce the risk of deteriorating its financial situation in the future, it must use preventive tools that can detect the company's impending financial problems in a timely manner. In this context, predictive models of the company's financial situation are used, which are part of the ex-ante financial analysis. The main task of these models is to assess the financial situation of the company and its future prospects in the context of its long-term presence in the market. In business practice, we recommend the use of a prediction model by company managers. Although this model fails to provide them with tools to deal with crises, it can act as a preventive system for early warning of imminent problems.

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