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# BANKRUPTCY PREDICTION MODEL DEVELOPMENT AND ITS IMPLICATIONS ON FINANCIAL PERFORMANCE IN SLOVAKIA

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**Abstract**

**Research purpose.** Financial distress being a global phenomenon makes it impact firms in all sectors of the economy and predicting corporate bankruptcy has become a crucial issue in economics. At the beginning of the last century, the first studies aimed to predict corporate bankruptcy were published. In Slovakia, however, several prediction models were developed with a significant delay. The main aim of this paper is to develop a model for predicting bankruptcy based on the financial information of 3,783 Slovak enterprises operating in the manufacturing and construction sectors in 2020 and 2021.

**Design / Methodology / Approach.** A prediction model that uses the appropriate financial indicators as predictors may be developed using multiple discriminant analysis. Multiple discriminant analysis is currently used in prediction model development. In this case, financial health is assessed using several variables that are weighted in order to maximise the difference between the average value calculated in the group of prosperous and non-prosperous firms. When developing a bankruptcy prediction model based on multiple discriminant analysis, it is crucial to determine the independent variables used as primary financial health predictors.

**Findings.** Due to the discriminant analysis results, the corporate debt level of the monitored firms may be regarded as appropriate. Despite the fact that the model identified 215 firms in financial distress due to an insufficient debt level, 3,568 out of 3,783 Slovak enterprises operating in the manufacturing and construction sectors did not have any problems with financing their debts. The self-financing ratio was identified in the developed model as the variable with the highest accuracy. Based on the results, the developed model has an overall discriminant ability of 93% since bankruptcy prediction models require strong discriminating abilities to be used in practice.

**Originality / Value / Practical implications.** The principal contribution of the paper is its application of the latest available data, which could help in more accurate financial stability predictions for firms during the current difficult period. Additionally, this is a ground-breaking research study in Slovakia that models the financial health of enterprises in the post-pandemic period.

**Keywords:** Bankruptcy; Prediction model; Multiple discriminant analysis; Manufacturing and construction sector; Slovakia.

**JEL codes:** G17; G33

## Introduction

Researchers from all over the world have become more interested in bankruptcy prediction during the past 50 years. The most accurate corporate failure prediction model has been the subject of several academic studies. When differentiating between prosperous and non-prosperous firms, authors frequently utilise the ultimate failure as the dividing line. However, financial distress has not yet been precisely defined. According to Dimitras et al. (1996), in previous and present studies of business failure prediction, researchers typically conduct their research by focusing on a few specific elements or stages

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of the business failure process based on their own expertise or interests. Whether a financial distress definition is applied in historical studies or a juridical definition of failure, such as bankruptcy, the criteria of failure are selected arbitrarily. Insolvency, default, and other related terms can be used to describe a business failure (Pan, 2012). Typically, operations of the firm discontinue when it encounters a business failure. As a result, a reliable bankruptcy prediction model's development is crucial for current corporate firms. Numerous bankruptcy prediction models have flooded the literature since Altman published one of the most well-known bankruptcy prediction models in 1968. It refers not just to the increasing number of papers published but also to the variety of models used to predict business failure. In recent years, a growing variety of different predictive models have been used in an effort to develop a bankruptcy prediction model that is more accurate due to the advancement of statistical techniques and information technology (Shi & Li, 2019).

The main aim of this paper is to develop a model for predicting bankruptcy based on the financial information of 3,783 Slovak enterprises operating in the manufacturing and construction sectors in 2020 and 2021, which are both critical years in the context of the COVID-19 pandemic and its consequences on the financial performance of enterprises. Thus, it is essential to develop bankruptcy prediction models that consider how well businesses performed financially throughout the crisis. Manufacturing in Slovakia is a measure of the output of firms in the industrial sector of the economy. It is one of the most significant sectors, whose production accounts for around 85% of total production. However, the construction sector, which is among the most significant not only in the Slovak Republic but also globally, is another significant sector. A prediction model that uses the appropriate financial indicators as predictors may be developed using multiple discriminant analysis. The principal contribution of the paper is its application of the latest available data, which could help in more accurate financial stability predictions for firms during the current difficult period. Additionally, this is a ground-breaking research study in Slovakia that models the financial health of enterprises in the post-pandemic period, i.e., in a volatile economic context. Since company insolvencies have risen above pre-pandemic levels, this research highlights the importance of the creation of bankruptcy prediction models that take into account the financial performance of enterprises in these sectors.

The paper is divided into the following sections. The literature review, which focuses on literature, familiarises the reader with the main theoretical background of the bankruptcy prediction model developed in previous studies since interest in them is high. The research methodology provides an overview of the financial data that serve as the primary input for constructing a prediction model, focusing on describing the methodological steps of multiple discriminant analysis. The third part presents the results of the developed model based on different financial ratios as well as the discussion in which the main findings are discussed and compared to other relevant studies published worldwide. Not only the most crucial outputs but the limitations and future research on this topic are described at the end of this paper.

## Literature review

The issue of business failure is not new, and the first research papers dealing with this topic appeared as early as the 1930s. Corporate failure was first addressed by Fitzpatrick (1932), who compared the development of indicators in solvent and insolvent firms. In the economic literature, the failure of enterprises is indicated by various terms, e. g. failure prediction, bankruptcy prediction, financial difficulties prediction, etc. The breakthrough period in corporate failure prediction was the second half of the last century. Beaver (1966) published the first paper devoted to future analysis and proved that financial indicators could be used even in anticipating the difficulties of business entities. The period in which this prediction model was created was specific primarily due to its static nature and simplicity in identifying the unique characteristics of firms in financial problems. Later, concurrently with the mathematical and statistical methods development, prediction models based on combinations of financial ratio indicators and other variables were developed. Such models account for the entirety of the financial situation of the firm in a single number, based on which it is possible to categorise a company as demonstrating or not a bankruptcy risk over a given period of time.

Research on the likelihood of financial distress after 1966 led to the development of new prediction models that could predict the probability of bankruptcy for each firm. Multivariate discrimination methods, which incorporate more factors in forecasting the enterprise development and indicate straightforward aspects of the corporate activity and to which weights of importance are assigned, were quite popular in the early stages of development (Horvathova et al., 2021). Altman's model is considered the most famous model created using multivariate discriminant analysis. Traditional ratio analysis is criticised by Altman (1968) as being prone to misunderstanding and potentially misleading. In the same paper, Altman introduces a ground-breaking prediction model, known as the Z-score, based on multivariate discriminant analysis that may predict corporate bankruptcy. Numerous financial experts have modified the original model in the past. In order to improve the predictive ability, several later studies verified the original and modified Altman model and revised the weights of the indicators. Many researchers have developed general models based on multivariate discriminant analysis that can be used by any enterprise, such as Bilderbeek (1979), Blum (1974), Daniel (1968), Deakin (1972), Laitinen (1991), Lussier et al. (1996), and many others. However, because these models cannot predict how likely a firm is to fail, their explanatory power is partially limited. Similarly, most studies in the past have shown that the basic assumptions for the multiple discriminant analysis are often violated.

Considering these problems, newer methods involving logit and probit analysis were created over time, which do not require these assumptions to be met. Like multiple discriminant analysis, logit and probit analysis, which assign weights according to their importance, use multiple variables for prediction. Generally, logistic regression is among the linear models, the link function between a linear combination of predictors and the dependent variable. The best-known author of logit models is Ohlson (1980), who was the first to apply logit analysis in bankruptcy prediction. Using logit analysis, Zavgren (1985) also created his prediction model, which focused primarily on manufacturing companies when creating the model, and Wang (2004) developed a logit model for internet companies. Zmijewski (1984) applied probit regression when creating a prediction model. Performance, leverage, and financial liquidity are crucial factors contributing to the Zmijewski score. The probit model, unlike the logit model, assumes a normalised normal distribution of the random variable. Logit and probit models have the strength of having a straightforward interpretation of the findings since the output of the given prediction models is an estimate of the likelihood of corporate bankruptcy in the future. Many authors have conducted studies aimed at comparing prediction models with models developed in the past. Lennox (1999) focused on comparing models developed using multiple discriminant analysis and conditional probability models. Kordlar and Nikbakth (2011) compared multidimensional discriminant analysis, logit and probit analysis models. In their study, Araghi and Makvandi (2013) pointed out the difference between the accuracy of the logit and probit models, while Ingram and Frazier (1982) focused on comparing the logit model compared to the MDA model. The new data analysis methods and technological progress development have been reflected in the prediction models' development. New statistical methods do not require the fulfilment of any assumptions, which makes them easily applicable to any data. Thus, when developing prediction models nowadays, it is possible to encounter the application of new techniques, such as neural networks (Odom & Sharda, 1990), genetic algorithms (Varetto, 1998), fuzzy logic (Chen et al., 2009), or support vector machines (Min & Lee, 2005). Despite the existence of many alternative models that have been created using a variety of methodologies to obtain the best results, many authors claim that it is still challenging to estimate bankruptcy risk. Nowadays, there are several prediction models developed globally that describe the conditions of the business environment (Hu, 2020; Kliestik et al., 2020; Kovacova et al., 2019; Kou et al., 2021; Valaskova et al., 2020; Zhang et al., 2021; and many others).

The COVID-19 pandemic has altered the complementary roles of planning and analysis for enterprises, as stated by Toth et al. (2022), and the emphasis has shifted away from planning and toward assessing the macroenvironment and the company's financial position. The impact of the pandemic on the financial performance of enterprises has been enormous, and it has arisen interest in financial health diagnostics and new bankruptcy prediction modelling. Tomczak (2021) claims that the significance of evaluating a company's and a sector's financial health has expanded as a result of COVID-19. Managers, lenders, and investors must accurately assess the financial health of the firms they oversee. However, the pandemic has also accelerated the reconfiguration of the reciprocal links between states and markets (Amankwah-Amoah et al., 2021). The study by Boratynska (2021) focuses on how local economies were affected

during the COVID-19 pandemic. When developing warning and recovery measures during the COVID-19 pandemic, business and restructuring professionals, financial institutions, and banking and public sectors' representatives may find it helpful to identify risk factors that determine the threat of corporate bankruptcy. Papik and Papikova (2023) highlight the importance of the bankruptcy model development (re-evaluation), as the performance of enterprises may be significantly weaker during the crisis periods. The consequences of the pandemic have forced researchers and academicians to develop new default predictors for small and medium-sized enterprises (e.g. Ciampi et al., 2021; Mirza et al., 2023), proposing some innovative approaches to improve the predictive ability of models. Moreover, the changes in the macroeconomic and microeconomic environment require modifications and searching for more precise methods of financial health prediction (Brygala, 2022).

In the era of increasing internationalisation and globalisation, bankruptcy prediction is crucial not only for firms but for other interested groups. There are many prediction models that differ in the approaches and methods required for their development, the complexity of the input data, the number of variables, and the way the results are interpreted. However, in general, the existence of a large number of models is due to the fact that there is no universal use in different industries and economic conditions.

## Research Methodology

The main aim of the paper is to develop a model for predicting the bankruptcy of Slovak enterprises operating in manufacturing (SK NACE 20, 21, 28, and 29) and construction sectors (SK NACE 41, 42, and 43) in 2020 and 2021 using appropriate quantitative methods. The production of firms as a part of the industrial sector of the Slovak economy is measured by manufacturing (Sujova et al., 2021). One of the most crucial industries in Slovakia, manufacturing contributes around 85% of the country's overall production. Construction is another crucial industry, ranking among the most significant not just in the Slovak Republic but worldwide (Spisakova et al., 2021). Generally, because it builds the infrastructure for cities, towns, and even countries, this industry is among the largest in the world. The coronavirus pandemic has lately impacted both of these significant businesses, severely affecting individual firms operating in the market.

For the prediction model development in Slovakia, the financial parameters from the ORBIS database, considered a source of business and financial data on more than 400 million private and public firms operating worldwide, were used as the input data. Financial data on 6,602 Slovak enterprises operating in the manufacturing and construction sectors in 2020 (for all independent variables, i.e., individual debt ratios) and 2021 (for the dependent variable, i.e., the corporate prosperity measured by the legislatively established limit value of the equity-to-debt ratio) were included in the dataset used to create the model. The firms that did not provide all the input data necessary for the crucial mathematical relationships determination during the monitored period were excluded from the created dataset since not all enterprises were suitable for the practical evaluation of financial ratios.

After the final adjustments (elimination of not available and outlying values), the final dataset comprises 3,783 enterprises; 2,592 operating in the manufacturing and 1,191 in the construction sector (982 small, 2,128 medium-sized and 673 large enterprises). Considering the legal form of enterprises, 88.76 % of the dataset are private limited companies, 10.26 % are public limited companies, and 0.98 % are companies of other legal forms. As the length of operation also plays an important role in the context of corporate competitiveness, financial stability and health, the dataset is formed of 34.13 % of enterprises established before the year 2000 and 65.87 % of enterprises were incorporated after the year 2000 (Bozkurt and Kaya, 2023). The descriptive statistics of variables entering the financial ratios indicators are summarised in Table 1.

**Table 1. Descriptive statistics of crucial financial data (in thousands. euros)**

| SK | TOAS | SHFD | CULI | NCLI | EBIT |
|---|---|---|---|---|---|
| **mean [€]** | 9,824.10 | 3,505.82 | 3,635.53 | 1,516.58 | 471.61 |
| **median [€]** | 1,540.79 | 477.61 | 640.00 | 119.48 | 56.29 |
| **st. dev. [€]** | 61,333.45 | 30,664.25 | 21,376.58 | 17,003.07 | 5,504.84 |

| | | | | | |
|---|---|---|---|---|---|
| **CV [%]** | 624.42 | 874.28 | 589.67 | 1,121.14 | 1,179.06 |
| **SK** | **DEBT** | **P/L** | **INTE** | **CF** | **DEPR** |
| **mean [€]** | 1,762.12 | 310.46 | 56.92 | 790.48 | 480.02 |
| **median [€]** | 261.95 | 31.58 | 7.37 | 110.68 | 79.10 |
| **st. dev. [€]** | 14,578.48 | 4,185.09 | 801.14 | 7,403.17 | 3,218.08 |
| **CV [%]** | 827.03 | 1,368.88 | 1,408.61 | 2,039.29 | 670.41 |

Note: TOAS total assets, SHFD shareholders' funds, CULI current liabilities, NCLI non-current liabilities, DEBT trade receivables, P/L net income, INTE interest paid, CF cash flow, DEPR depreciation and amortisation

Subsequently, the multiple discriminant analysis was used for the prediction model development, and its objective is to model one quantitative variable (i.e., a dependent variable) as a linear combination of other variables (i.e., independent variables). It is possible to use discriminant analysis if the classifications of the groups in the dependent variable (Y) are affected by at least one of the independent variables (X) while the following hypotheses are proposed:

H0: The dependent variable (Y) does not depend on any independent variables (Xi's).

H1: The dependent variable (Y) depends on at least one of the independent variables (Xi's).

The multivariate discriminant analysis was performed in these methodological steps: i) the data is thought to be roughly multivariate normally distributed since the sample size of the examined variables is big enough (multivariate central limit theorem); ii) by employing group averages and the outcomes of the ANOVA, the discriminant analysis may forecast group membership and detect any relevant differences between groups on any of the independent variables. The variable is probably statistically insignificant if the p-value exceeds the selected significance level (0.05); iii) the assumption of this method that the groups' variance-covariance matrices are equal is tested by the Box's M test; iv) the relationship between the groups in the dependent variable and the discriminant function is assessed by the canonical correlation measures (Eigenvalue and Wilk's lambda); v) the identification of the best discriminants of corporate financial health prosperity is realised by the values of the standardised canonical discriminant function and correlation coefficients; vi) the formation of the discriminant model, Z score equation, using the unstandardised discriminant function coefficient.

Generally, the financial health of a firm is evaluated using several ratios that are weighted to maximise the difference between the average value determined in the group of prosperous and non-prosperous enterprises. Based on the ratios mentioned by top researchers (Bellovary et al., 2007; Dimitras et al., 1996; Gregova et al., 2020; Kliestik et al., 2020; Kovacova et al., 2019), it is necessary to determine the independent variables as the primary predictors of financial health. The selected debt ratios and the relationships needed for the calculation are listed in Table 2.

**Table 2. Summarised formulas of debt indicators** (Source: Valaskova et al., 2021)

| | **Ratio** | **Algorithm** |
|---|---|---|
| X01 | Total indebtedness ratio | Current and non-current liabilities to total assets |
| X02 | Self-financing ratio | Shareholders' funds to total assets |
| X03 | Current indebtedness ratio | Current liabilities to total assets |
| X04 | Non-current indebtedness ratio | Non-current liabilities to total assets |
| X05 | Debt-to-equity ratio | Current and non-current liabilities to shareholders' funds |
| X06 | Interest burden ratio | Interests paid to earnings before interest and taxes |
| X07 | Interest coverage ratio | Earnings before interest and taxes to interests paid |
| X08 | Debt-to-cash-flow ratio | Current and non-current liabilities to cash flow |
| X09 | Equity leverage ratio | Total assets to shareholders funds |
| X10 | Financial independence ratio | Shareholders' funds to current and non-current liabilities |
| X11 | Non-current assets coverage ratio | Shareholders' fund and non-current liabilities to non-current assets |
| X12 | Insolvency ratio | Current and non-current liabilities to receivables |

The individual enterprises used to create a discriminatory model had to be divided into two relevant groups. The first group consisted of enterprises with the appropriate level of debt without significant

financial difficulties, whereas the second group included more indebted firms with crucial financial distress. The discriminatory model was developed using the statute of the company in crisis, which states that if the equity-to-debt ratio, which symbolises the deteriorating degree of the financial independence of the enterprise, is less than 0.08, a firm is in a crisis (Kliestik et al., 2020; Gregova et al., 2020). The level of debt is inappropriately high, and the firm is in financial difficulties if the equity-to-debt ratio falls below this level. However, if this ratio exceeds the limit, the enterprise is not having significant financial problems. IBM SPSS Statistics software was used to perform the calculations and model development.

## Research results

There are two possible future development strategies for the dependent variable: non-prosperous enterprise (marked by 0) and prosperous enterprise (marked by 1). The final dataset includes financial information on 3,783 Slovak enterprises classified into 3,568 prosperous enterprises and 215 non-prosperous enterprises.

Since multivariate discriminant analysis may be used to predict group membership, it is required to examine group averages and data from the ANOVA results to determine whether any significant differences exist between groups for any independent variables. According to the tests of equality of group means table (Table 3), it is not worthwhile continuing the investigation if there are no substantial group differences.

**Table 3. Test of equality of group means** (Source: own elaboration)

| Tests of Equality of Group Means | | | | | |
|---|---|---|---|---|---|
| | **Wilks' Lambda** | **Sig.** | | **Wilks' Lambda** | **Sig.** |
| X01_2020 | 0.985 | 0.000 | X08_2020 | 1.000 | 0.645 |
| X02_2020 | 0.959 | 0.000 | X09_2020 | 1.000 | 0.648 |
| X03_2020 | 0.981 | 0.000 | X10_2020 | 0.989 | 0.000 |
| X04_2020 | 0.997 | 0.001 | X11_2020 | 0.999 | 0.024 |
| X05_2020 | 1.000 | 0.613 | X12_2020 | 0.999 | 0.024 |
| X06_2020 | 1.000 | 0.957 | size=large | 0.995 | 0.000 |
| X07_2020 | 1.000 | 0.662 | size=medium-sized | 0.999 | 0.024 |

Based on the results in the table, it can be concluded that all variables considered as statistical indicators may be used as the suitable discriminator, except for X05, X06, X07, X08 and X09.

The variance-covariance matrices are assumed to be identical in the multivariate discriminant analysis as a fundamental assumption. Box's M evaluates the null hypothesis that there is no difference in the covariance matrices among the dependent groups. Table 4 summarises the log determinants results. Although the log determinants of the variance-covariance matrices of each group differ, they should be equal.

**Table 4. Log determinants table** (Source: own elaboration)

| Log Determinants | | |
|---|---|---|
| **Y_2021** | **Rank** | **Log Determinant** |
| 0 | 7 | 16.802 |
| 1 | 7 | 9.030 |
| Pooled within-groups | 7 | 10.987 |
| The ranks and natural logarithms of determinants printed are those of the group covariance matrices. | | |

When using Box's M (Table 5) to test for similarity and the existence of significant differences, a non-significant M is considered. In the SPSS calculation, the presumption of different covariance matrices was used since Box's M cannot be regarded as identical in this circumstance.

**Table 5. Box's M test results table** (Source: own elaboration)

| Test Results | | |
|---|---|---|
| Box's M | | 5,734.855 |
| F | Approx. | 202.443 |
| | df1 | 28 |
| | df2 | 470,660.199 |
| | Sig. | 0.000 |
| Tests null hypothesis of equal population covariance matrices. | | |

The multiple correlation between the predictors and the discriminant function is the canonical correlation, which provides a metric for the overall model fit and is considered the amount of variance explained ($R^2$). Table 6 summarises the canonical correlation results mutually with Wilk's Lambda, which emphasises the significance of the discriminant function. Despite the relatively low value of canonical correlation for Slovak enterprises (0.362), the model suggests a statistically significant canonical correlation.

**Table 6. Eigenvalues and Wilk's Lambda table** (Source: own elaboration)

| Eigenvalues | | | | |
|---|---|---|---|---|
| **Function** | **Eigenvalue** | **% of Variance** | **Cumulative %** | **Canonical Correlation** |
| 1 | 0.151 | 100.0 | 100.0 | 0.362 |
| **Wilk's Lambda** | | | | |
| **Test of Function(s)** | **Wilks' Lambda** | **Chi-square** | **df** | **Sig.** |
| 1 | 0.869 | 530.555 | 7 | 0.000 |

The discriminant coefficients (or weights) are used similarly to multiple regression. The relevance of each predictor (the sign reflects the direction of the relationship) is summarised in Table 7, much like what the multiple regression's standardised regression coefficients (beta's) accomplished. The self-financing ratio is one of the most crucial determinants of allocation to enterprises with or without financial difficulties with the best discriminating ability. Slightly worse discriminators are the variables' current indebtedness ratio and financial independence ratio. The developed prediction model likewise heavily weights indicators that relate to the firm size.

**Table 7. Standardised canonical discriminant function coefficients table** (Source: own elaboration)

| Standardised Canonical Discriminant Function Coefficients | |
|---|---|
| | **Function** |
| | **1** |
| X01_2020 | 0.191 |
| X02_2020 | -0.890 |
| X03_2020 | 0.597 |
| X10_2020 | 0.614 |
| X12_2020 | 0.098 |
| size=large | -0.276 |
| size=medium-sized | -0.253 |

The canonical structure matrix shows the correlations between each variable in the model and the discriminant functions. As an additional method for depicting the relative importance of the predictors, Table 8 provides the values of the correlation coefficients between the various independent variables and the discrimination function. The self-financing ratio is the best discriminator even when considering correlation coefficients because this ratio and the discrimination function have the highest correlation. The current indebtedness ratio and the total indebtedness ratio can be considered as other statistically significant variables. The threshold between significant and insignificant variables is typically set at 0.3, while these mentioned variables reached this value.

The non-standard coefficients of the canonical discriminant function can be used to determine the discriminant score of the prediction model for each Slovak enterprise operating in the manufacturing and construction sectors.

$$y_{SK} = 0.165 + 0.123X_1 - 1.130X_2 + 0.642X_3 + 0.232X_{10} - 0.723size_{large} - 0.511size_{medium-sized} \quad (1)$$

The discriminant function coefficients indicate how each variable contributes prejudicially to the discriminant function, which corrects all other variables in the equation. The categorical variables of size=large and size=medium-sized are introduced into the discriminant function analysis using dummy variables.

**Table 8. Structure matrix table** (Source: own elaboration)

| Structure Matrix | | | |
|---|---|---|---|
| | **Function** | | **Function** |
| | **1** | | **1** |
| X01_2020 | 0.317 | X08_2020[a] | 0.038 |
| X02_2020 | -0.531 | X09_2020[a] | 0.003 |
| X03_2020 | 0.359 | X10_2020 | 0.277 |
| X04_2020[a] | 0.145 | X11_2020[a] | -0.016 |
| X05_2020[a] | 0.002 | X12_2020[a] | 0.095 |
| X06_2020[a] | 0.010 | size=large | -0.179 |
| X07_2020[a] | -0.024 | size=medium-sized | -0.095 |
| They pooled within-group correlations between discriminating variables and standardised canonical discriminant functions. Variables are ordered by the absolute size of correlation within the function.<br>This variable was not used in the analysis. | | | |

Because SPSS utilises the model constant to perform an intended modification for centroid calculations, the weighted average of the centroid (weighted by the number of firms in the individual groups) is zero. The Z-score value may be compared to zero in this case; a positive number indicates a less prosperous organisation, whereas a negative number indicates a financially sound business. However, having enough discriminating abilities is required for the prediction model to be used in practice. Based on the classification table (Table 9), it is evident that 93% of the enterprises were correctly classified into one of the two considered groups.

**Table 9. Classification results table** (Source: own elaboration)

| Classification Results | | | | | |
|---|---|---|---|---|---|
| | | | **Predicted Group Membership** | | |
| | | Y_2021 | 0 | 1 | Total |
| Original | Count | 0 | 121 | 94 | 215 |
| | | 1 | 172 | 3,396 | 3,568 |
| | % | 0 | 56.3 | 43.7 | 100.0 |
| | | 1 | 4.8 | 95.2 | 100.0 |
| For SK, 93.0% of original grouped cases were correctly classified. | | | | | |

Despite several models that have been developed using various techniques to obtain the best outcomes, many authors contend that it is still challenging to predict bankruptcy risk. Many prediction models that describe the aspects of the business environment were developed with a significant time gap in Slovakia as well.

In Slovakia, the development of a prediction model was initially addressed by Chrastinova (1998) and Gurcik (2002), who used multiple discriminant analysis to create a model for agricultural enterprises. To evaluate the future corporate prosperity of non-financial small and medium-sized enterprises, Hurtosova (2009) used logistic regression for the first time in the Slovak national context. An overview of bankruptcy prediction research is provided by Delina and Packova (2013), which chose three bankruptcy prediction models for the verification of data from Slovak enterprises. The authors applied

regression analysis to develop a modified model with higher predictive performance than the original models. Based on data mining validation methods, they have proposed an approach to validate the performance of chosen bankruptcy prediction models. Sofrankova (2014) also concentrated on the description of selected prediction models in her study, which may detect early deterioration of the firm's financial situation. Kubicova and Faltus (2014) tested the resolution ability of indicators that included income tax components as well as the predictive ability of the bankruptcy prediction model using data from Slovak enterprises. Mihalovic (2016) focused on the bankruptcy prediction model development based on two various statistical methods. These include both the logistic regression function and the multiple discriminant function because financial ratios may be the best way for enterprises to identify between prosperous and non-prosperous firms. Adamko and Svabova (2016) studied the predictive ability of the global Altman's model using a dataset of Slovak enterprises. In order to create a model that is superior to those already in use in the Slovak business environment, Gavurova et al. (2017) evaluated the effect of including trend variables on model development and using decision trees in addition to discriminant analysis.

Consequently, a model with a prediction accuracy close to 85% was suggested using decision trees. In order to develop models for predicting bankruptcy in Slovak firms, Kovacova and Kliestik (2017) applied the logit and probit techniques. The findings indicate that the logit-based model performs somewhat better than the classification accuracy of the probit-based model. However, many other authors also dealt with the issue of creating prediction models in the conditions of Slovakia, such as Boda and Uradnicek (2019), Kliestik et al. (2020), Kovacova et al. (2019), Svabova et al. (2020), Valaskova et al. (2020), Valaskova et al. (2018), and many others.

When comparing the model developed for predicting bankruptcy for Slovak enterprises operating in the manufacturing and construction sectors in 2020 and 2021, financial indicators were used with a focus on monitoring the level of indebtedness, while the self-financing ratio, current indebtedness ratio, and financial independence ratio can be considered the most important predictors. Valaskova et al. (2018) determined the financial predictors that are crucial to the process of quantifying corporate prosperity and detecting financial threats according to the results of the multiple linear regression analysis. The final notation of the prosperity quantification model included six variables, with the current liabilities to total assets ratio being one of the most important indicators of financial prosperity. Boda and Uradnicek (2019) critically validated the usefulness of three prediction models that are used or were developed for predicting the financial distress of Slovak agricultural enterprises and identified three indicators: gross return on revenue, debt ratio, and days payables outstanding, which are associated with liquidity and solvency through revenue profitability, capital structure, and cash management discipline, respectively. Kovacova et al. (2019) presented in-depth insight and analysis of bankruptcy prediction models developed in the Visegrad Group countries, and based on the results, total liabilities to total assets and shareholders' funds to total assets are the most often regarded significant predictors in Slovakia. Kliestik et al. (2020) also concentrated on an in-depth mutual comparison of the developed prediction models in the conditions of Visegrad Group countries, pointing out that the most commonly used debt indicators are total liabilities to total assets, shareholders' funds to total assets, cash flow to total liabilities, and shareholders' funds to total liabilities. As a result of the previous, major indicators of indebtedness were regarded significant discriminants of financial difficulties in the developed prediction models even before the outbreak of the COVID-19 pandemic. The use of the ratio of current liabilities to total assets in financial stability modelling has a positive perspective because this ratio is related to bankruptcy, indicating a greater probability of financial failure achieving a higher value of the ratio (Valaskova et al., 2020). Not only current liabilities to total assets but also shareholders' funds to total assets and shareholders' funds to total liabilities have a considerable impact on predicting the financial distress of firms. Ptak-Chmielewska (2021) checked and validated the effect of the financial crisis on bankruptcy prediction. The results showed that current liquidity, gross margin ratio, operating profitability of sales, and asset turnover are the most important explanatory factors in bankruptcy prediction. As declared by Matejic et al. (2022), compared to the pre-COVID-19 period, the chance of bankruptcy will continue to be high, making the remaining businesses more susceptible to future exogenous developments. The specific interest in the manufacturing sector is presented in the research by Pacheco et al. (2022), who also affirmed that estimates using financial information closest to the bankruptcy period could enhance the predictive power of the model. However, given these new circumstances into consideration, the

present bankruptcy prediction models should be revalidated and adjusted to current market conditions. The significance of research outcomes for the academic community, financial institutions, stakeholders, and other interested parties is therefore highlighted, and the added value of the study outputs can be presented. Identifying key financial health predictors in a specific sector of the economy may be, however, perceived as a relevant contribution to the existing theoretical framework. A key element of strategic management is the ability of managers to foresee future events and business performance and the use of bankruptcy predictors as a basis for the decision-making process. Thus, predicting bankruptcy is more important than ever because it is one of the biggest threats to a company's existence.

## Conclusions

The effectiveness of each model for predicting corporate bankruptcy depends on the data used as input and the processing method applied. However, these models are built based on empirical data from a particular economy. Only the economy from which empirical data was gathered during model development is typically able to use it successfully. Furthermore, it is hard to treat any one model as immutable or stable since its prediction ability may deteriorate due to changes in economic conditions in the country.

The main aim of this paper was to develop a model for predicting bankruptcy based on the financial information of 3,783 Slovak enterprises operating in the manufacturing and construction sectors in 2020 and 2021. Due to the discriminant analysis results, the corporate debt level of the monitored firms may be regarded as optimum. While the model identified 215 firms in financial distress due to an unacceptable level of debt, 3,568 out of 3,783 Slovak enterprises operating in the manufacturing and construction sectors did not have any problems with financing their obligations. The self-financing ratio, one of the most significant predictors of allocation to the group of firms with or without financial difficulties, stood up as the variable in the developed model with the best discriminating power. However, the current indebtedness ratio, the total indebtedness ratio, and the financial independence ratio can be considered other statistically significant variables. Generally, the model requires sufficient discriminating abilities to be applied in practice. The classification matrix, also known as the confusion matrix, provides this output by identifying the percentage of existing data points out that the model is correctly classified. It is evident from the results that the developed model has an overall discriminant ability higher than 93%.

The following limitation needs to be highlighted despite the contribution of this paper to the extant literature and its practical implications for the accurate prediction of future financial stability and development. The study has several limitations, such as the findings of the multiple discriminant analysis may not be comprehended, as well as those obtained using other techniques, such as logistic regression or neural networks. Future research should involve more investigation to determine which method provides more accurate and precise outputs when predicting corporate financial health.

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