Gajdosikova, D., Valaskova, K., & Kliestik, T. (2025). Predicting bankruptcy and ensuring financial sustainability: A focus on Visegrad economies. *Journal of International Studies, 18*(3), 122-143. doi:10.14254/2071-8330.2025/18-3/7

Journal of International Studies

Centre of Sociological Research

Scientific Papers

Predicting bankruptcy and ensuring financial sustainability: A focus on Visegrad economies

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Abstract. Bankruptcy prediction lies in the need for financial institutions, investors, and stakeholders to assess the financial health and solvency of companies. Bankruptcy prediction models aim to forecast the likelihood of a business facing financial distress or going bankrupt in the future. The main aim of the paper is to build a bankruptcy prediction model utilizing financial information from 12,816 business entities in the Visegrad Group countries. Because multiple discriminant analysis provides important insights into corporate financial health, it is possible to develop individual prediction models for each Visegrad Group country as well as a comprehensive model for the entire group. Relevant debt ratios are crucial components of bankruptcy prediction models. The development of bankruptcy prediction models significantly enriches the theory and practice of corporate finance by offering valuable insights, improving decision-making processes, and enhancing risk management and it also provides insightful information on how different crises affect prediction models, especially when comparing the COVID-19 crisis model to previous models developed in a comparable way.

Received: November, 2024
1st Revision: August, 2025
Accepted: September, 2025

DOI: 10.14254/2071-8330.2025/18-3/7

Keywords: bankruptcy prediction, corporate performance, COVID-19, Visegrad countries

JEL Classification: G01, G33, M21

1. INTRODUCTION

Bankruptcy prediction models should respond to financial distress, which is a state of a business that is the opposite extreme of financial health. Financial distress is typically defined as a state in which a firm exhibits severe payment problems that it can no longer address other than through a radical change in its operations or structure. The predictive analysis was primarily driven by the effort to forecast corporate financial development and, based on that, prevent potential bankruptcy. Individual authors tested the predictive ability of dozens of indicators that they assumed could predict insolvency. The original selection for practical use narrowed down to a relatively small number of financial indicators with appropriate discriminatory ability. These indicators are characterized by having different levels in prosperous and non-prosperous businesses and a different development long before the acute onset of a crisis.

In the past, the use of indebtedness indicators in bankruptcy prediction models has been a common practice. Banking stability indicators and market valuation metrics have gained increasing attention in financial distress prediction research (Abbas & Hassouni, 2024). These indebtedness indicators serve as essential components that offer insights into financial health, risk, and corporate solvency (Sardo et al., 2022). Historically, researchers have recognized the importance of understanding a corporate debt profile in forecasting its financial stability. Indicators such as debt ratios, leverage ratios, and interest coverage ratios have been prevalent in these prediction models. These models aim to capture the complex interplay between a corporate financial structure, performance, and the potential for financial distress (Kovacova et al., 2022; Dankiewicz et al., 2022). In summary, the incorporation of debt indicators in bankruptcy prediction models has a rich history, reflecting the recognition of the significant role that debt-related metrics play in assessing the financial viability and risk of companies.

The primary objective of this paper is to create a bankruptcy prediction model using financial data from 12,816 enterprises within the Visegrad Group countries. Employing multiple discriminant analysis, individual prediction models for each Visegrad Group country, and a comprehensive model for the entire Visegrad Group can be developed, incorporating relevant debt ratios as critical components of bankruptcy prediction models because of valuable insights into corporate financial health. The primary contribution of this study lies in utilizing the latest available data, enhancing the accuracy of predicting the financial stability of enterprises during the current challenging period. The development of the model offers valuable insights into understanding how various crises impact prediction models, particularly through comparisons between COVID-19 crisis models and earlier ones established in a similar context (considering predictors and their coefficients). Additionally, this research is groundbreaking in the Visegrad Group countries, focusing on modelling the financial health of enterprises in the post-pandemic era and addressing a research gap in the evolution of bankruptcy prediction models and the utilization of relevant financial ratios in economically unstable environments. Given the increase in business insolvencies beyond pre-pandemic levels, this study adds value by creating bankruptcy prediction models that reflect the financial performance of enterprises during crisis periods. It is crucial to explore anomalies in businesses experiencing a decline in financial stability, especially given the observed changes in bankruptcy risks over time (Mazanec et al., 2022). It has been suggested that anomalies, particularly extreme values, could deviate significantly from the overall model outcome, leading to potential misclassification in bankruptcy assessments, which could result in businesses facing financial distress being incorrectly identified as financially stable, or conversely, businesses with certain extreme values that are financially robust might be erroneously categorized as facing bankruptcy. However, current bankruptcy prediction models are deemed unsatisfactory and require revalidation, especially in the Visegrad region.

The paper is structured into the following sections. The literature review, focused on literature research, familiarizes the reader with the fundamental theoretical foundation of bankruptcy prediction model development in previous studies, given the heightened interest in these models. The research methodology section provides a summary of financial data, which serves as the primary foundation for developing a prediction model, along with an explanation of the methodological steps involved in multiple discriminant analysis. The third section outlines the results obtained from the developed model based on debt ratios, utilized as one of the input variables in the analysis. In the discussion section, the primary findings are clarified and compared to relevant studies worldwide. The conclusion not only highlights the essential outcomes but also addresses the limitations and suggests avenues for future research on this topic.

2. LITERATURE REVIEW

The advancement of statistical programs towards the end of the previous century broadened the scope of empirical research (Abdullah, 2021). The models that emerged during this period, drawing on observations from thousands of businesses, generally exhibit greater effectiveness. Over the last two decades, there has been a shift in the popularity of bankruptcy prediction tools from statistical approaches to intelligent ones. In contrast to traditional statistical methods, the novel techniques for model development do not necessitate adherence to specific assumptions. Consequently, they can be applied to diverse datasets, suggesting that they may outperform conventional statistical approaches. These techniques, including genetic algorithms (Varetto, 1998; Shin & Lee, 2002), fuzzy logic (Chen et al., 2009; Korol, 2018), or support vector machines (Min & Lee, 2005; Kim & Sohn, 2010), exhibit greater computational complexity and often necessitate the use of statistical programs, but they demonstrate higher accuracy in estimating the likelihood of bankruptcy.

The effectiveness of individual models in predicting corporate bankruptcy relies not only on the processing technique employed but the input data. Debt ratios are critical components of bankruptcy prediction models because they offer valuable insights into a company's financial structure, risk exposure, and overall financial health (Ciocirlan et al., 2023; Letkovksa et al., 2023). Including these ratios enhances the accuracy and reliability of models designed to assess the likelihood of bankruptcy. Including debt ratios in a bankruptcy prediction model is important for several reasons. Sardo et al. (2022) conclude that high levels of debt relative to equity may indicate financial distress, as the company may struggle to meet its debt obligations. According to Daskalakis et al. (2017), Kristofik & Slampiakova (2021) and Issa et al. (2022), debt ratios help assess the level of financial leverage a company has taken on, however, high levels of leverage can amplify the impact of financial downturns, making a company more vulnerable to economic shocks and increasing the likelihood of bankruptcy. If corporate earnings are insufficient to cover interest payments, it may face liquidity issues, increasing the risk of bankruptcy (Uysal, 2011; Musa et al., 2025). Generally, investors and creditors use debt ratios to evaluate the risk associated with a company and Klepac and Hampel (2017) point out that including debt ratios in bankruptcy prediction models provides a more comprehensive view of the corporate financial position, aiding stakeholders in making informed decisions. High levels of debt can negatively impact also a credit rating of the enterprise and market perception. As stated by Baranova et al. (2018), a deterioration in creditworthiness may lead to higher borrowing costs or difficulty in accessing credit, further exacerbating financial difficulties. In general, debt ratios contribute valuable information that enhances the overall predictive power of bankruptcy models (Konieva & Stavarek, 2023). Models that incorporate a wide range of financial metrics, including debt ratios, are often more accurate in identifying companies at risk of financial distress. According to Ehikioya & Omankhanlen (2021), economic conditions can also impact a corporate ability to manage its debt. Capital structure decisions during crisis periods significantly impact corporate financial stability, particularly for mature SMEs where profitability, guarantees, and trade credit relationships become critical determinants of debt optimization strategies (Adair & Adaskou, 2018). Including debt ratios in a bankruptcy prediction model helps account for external factors that may affect a financial stability of the enterprise. Vochozka et al. (2016) highlight that debt ratios, when considered alongside other financial metrics, provide a more comprehensive picture of a corporate financial health. This holistic approach improves the ability to identify warning signs of financial distress. The predictive ability of the model may also be impacted by the financial indicators used, which offer crucial insights into the financial condition and performance of the firm (Wang et al., 2023). Leverage ratios offer insights into the extent to which a company finances its investments using funds from sources other than its owners, and lower leverage ratios are characteristic of prosperous enterprises (Sundgren, 2000). Non-prosperous enterprises are expected to exhibit higher financial leverage than healthy ones, as the inability to meet substantial fixed debt service obligations often contributes to corporate failure (Reddy et al., 2022). The probability of bankruptcy is positively correlated with leverage ratios (Correia & Poblacion, 2015). Hui et al. (2012) assert that financial leverage variables exhibit robust discriminatory power, and the primary reason for corporate failure lies in their incapacity to meet substantial debt obligations. The debt ratio, the initial indicator gauging a corporate indebtedness, was utilized by Mazanec et al. (2022), who retained it as one of the four variables in their logit model for predicting bankruptcy. A higher total debt to total assets ratio signifies heavy reliance on debt capital for asset financing, thereby increasing the likelihood of financial distress (Bui & Thach, 2023). Standar & Kozera (2020) highlighted the significant discriminating power of the debt ratio in the logit model. Among the three predictor variables included in the final multivariate model by Hui et al. (2012), the debt ratio emerged as the most significant. In line with these findings, the debt ratio is positively correlated with the probability of bankruptcy.

Research in this area often focuses on refining the choice and combination of these ratios, exploring non-linear relationships, and incorporating additional factors for a more accurate prediction. The challenge lies in striking a balance between the simplicity needed for interpretability and the complexity necessary for capturing the nuances of financial distress. It's important to note that while debt ratios are valuable indicators, a comprehensive bankruptcy prediction model often considers a variety of financial and non-financial factors to provide a more robust assessment of a company's risk of bankruptcy. Additionally, the effectiveness of specific ratios may vary across industries, so customization may be required based on the nature of the business.

3. METHODOLOGY

The input data for the prediction model development for the Visegrad Group countries was provided by the ORBIS database, recognized as a source of business and financial data on more than 400 million private and public enterprises operating globally. The dataset used to develop the model encompassed financial data on 100,057 enterprises operating in Visegrad Group countries in 2021 (for all independent variables, i.e., individual financial indicators) and 2022 (for the dependent variable, i.e., corporate prosperity). The Visegrad Group countries present unique sustainability challenges, particularly in balancing economic performance with environmental considerations, as evidenced by significant variations in sustainability indicators across these regions (Drożdż et al., 2023). However, due to the unsuitability of some enterprises for the practical evaluation of financial indicators, the data retrieved from the database had to be appropriately adjusted. Corporations that did not provide all the necessary input data for the critical mathematical formula calculation during the monitored period were excluded from the dataset, reducing the reporting power of the obtained results. According to Nyitrai & Virag (2019), financial indicators are commonly used as explanatory variables in bankruptcy prediction models. These metrics frequently display a skewed distribution due to the existence of outliers. The literature employs various ad hoc approaches to identify and address extreme values in the absence of a clear definition of outliers. However, the impact of these diverse approaches on the predictive accuracy of models remains uncertain. While there is agreement in the literature regarding the importance of addressing outliers, defining which values qualify as extreme and should be addressed to maximize the predictive power of models remains unclear. For this reason, the dataset underwent the removal of its outlying values to enhance the informativeness of the results derived from the computed debt analysis using the Z-Score method. Employing this approach enables the determination of the difference between each receive signal strength observation and the time-series mean receive signal strength observation. Subsequently, the result is divided by the standard deviation of the observation. A Z-Score of 0 signifies equality between the mean of the time-series observation and the receive signal strength observation. Positive and negative Z-Scores indicate that the received signal strength measurement is positioned above and below the mean, respectively. An observation of receive signal strength is labeled an outlier when its Z-Score value exceeds an established threshold. Typically, the most commonly used threshold for outlier detection is ±3, as indicated by Ciccione et al. (2023). Thus, in this research paper, any receive signal strength observation with a Z-Score value exceeding ±3 was designated as an outlier. After the final adjustments (elimination of not available and outlying values), the dataset consists of 12,816 enterprises used in the prediction model development.

The data required for the prediction model development in the Visegrad Group countries is encompassed in the final dataset. In accordance with the criteria established in the ORBIS database for determining firm size characteristics, a very large enterprise is defined as one that satisfies at least one of the subsequent conditions: operating revenue ≥ 100 million EUR, total assets ≥ 200 million EUR, and employees ≥ 1,000. A large enterprise is categorized as having an operating revenue ≥ 10 million EUR, total assets ≥ 20 million EUR, and employees ≥ 150. A medium-sized enterprise is one that fulfills at least one of the following criteria: operating revenue ≥ 1 million EUR, total assets ≥ 2 million, and employees ≥ 15. Enterprises that do not meet these criteria are classified as small enterprises. The final dataset, taking firm size into account, comprises 626 very large enterprises, 2,588 large enterprises, 6,790 medium-sized enterprises, and 2,812 small enterprises. The ORBIS database delineates the following legal form categories. The final dataset contains 1,492 public limited companies with capital divided into shares that may be offered to the general public and whose members are only liable for the corporate debts up to the amount owed on their shares; 10,169 private limited companies with capital divided into shares that are not accessible to the general public; 1,093 partnerships, where at least one partner is personally responsible for the corporate debts; and 62 enterprises with other legal forms.

For the definition of the most significant predictor and the best discriminants of corporate financial prosperity, as well as for the development of models for individual countries within the Visegrad Group countries and a comprehensive model in the conditions of these countries, it is necessary to focus on quantifying the financial performance of enterprises. The construction of such a discriminator is contingent not only on the appropriately distinguishing financial indicator selection but also on knowledge of methods that allow their aggregation (Situm, 2014). Currently, in the development of prediction models, multidimensional discriminant analysis, also known as Z-score analysis in the professional literature, is primarily used. Discriminant analysis is one of the oldest methods for discriminating objects, capable of distinguishing existing groups of statistical units within the underlying dataset and subsequently formulating classification rules for their inclusion in the created groups.

The application of multidimensional discriminant analysis in the analysis and evaluation of corporate financial prosperity aims to achieve the best possible classification of the evaluated firm into either prospering or non-prospering enterprises. The classification of a company into one of the two created groups is assessed through numerous financial indicators, to which specific weights are assigned in order to maximize the difference between the average value calculated in the group of prospering and non-prospering enterprises. Identifying whether or not at least one of the independent variables (X) has an impact on the group classifications in the dependent variable (Y) is the primary objective of discriminant analysis, based on which 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).

While there are currently statistical methods that offer more precise results, discriminant analysis, in particular, is relatively straightforward to interpret and can be utilized at a minimum as a benchmark in model creation.

It is essential to determine the independent variables utilized for the prediction model development as the primary predictors of financial health. The selected debt indicators and the relationships needed for their calculation are summarized in Table 1.

Table 1

Summarized formulas of financial indicators

	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 coverage ratio	Earnings before interest and taxes to interests paid
X07	Interest burden ratio	Interests paid to earnings before interest and taxes
X08	Debt-to-cash-flow ratio	Current and non-current liabilities to cash flow
X09	Equity leverage ratio	Total assets to shareholders funds
X10	Insolvency ratio	Current and non-current liabilities to receivables

Source: own elaboration.

The individual enterprises used for the prediction model development need to be classified into two relevant groups. The first group comprises prospering firms with a reasonable level of debt and without significant financial difficulties. Conversely, the second group consists of enterprises with a higher level of debt that also experience financial difficulties. In general, the basis for constructing the discriminant model relies on the status of the company in crisis, from which it follows that a firm faces financial difficulties if the ratio of equity to debt, representing a declining level of financial independence and corporate creditworthiness, falls below 0.08. If the ratio of equity to debt is below this threshold, the level of indebtedness is not reasonable, and the company is in financial crisis (Papik & Papikova, 2023).

Regarding the dependent variable, there are two conceivable future developments of the economic prosperity of the firm: non-prospering enterprises (marked as 0) and prospering enterprises (marked as 1). The dataset necessary for the construct of the discriminant model includes information on:

- 6,048 Slovak enterprises, which are divided into 5,796 prospering enterprises and 252 non-prospering enterprises,
- 1,626 Czech enterprises consisting of 1,604 prospering enterprises and 22 non-prospering enterprises,
- 3,851 Polish enterprises, categorized into 3,790 prospering enterprises and 61 non-prospering enterprises,

- 1,291 Hungarian enterprises, comprising 1,279 prospering enterprises and 12 non-prospering enterprises.

The multivariate discriminant analysis involves several methodological steps and the following steps were pursued in this research paper:

1. A suitably sized sample, according to certain rules of sample size determination, must be identified. The dataset should consist of a minimum of five examples for each independent variable, with at least 20 cases being appropriate.

2. Utilising group averages and ANOVA findings, discriminant analysis may predict group membership and discern significant differences across groups for the independent variables. An analysis of the equivalence of group means is performed. If the p-value above the designated significance level, it suggests that the variable probably does not meaningfully contribute to the model.

3. Box's M evaluates the hypothesis of homogeneity of variance-covariance matrices across the groups. A significant Box's M value coupled with a low p-value indicates a breach of this assumption. Nonetheless, Box's M normally escalates with a considerable sample size.

4. Canonical correlation evaluates the relationship between the dependent variable groups and the discriminant function, utilising two metrics: Eigenvalue and Wilks' lambda. Eigenvalue, commonly known as characteristic roots, signifies the proportion of explained to unexplained variation in a model. Elevated eigenvalues signify enhanced functionality. Wilk's Lambda, a mathematical expression of one minus the explained variation, is utilised to determine the importance of discriminant functions.

5. It is necessary to evaluate the standardised canonical discriminant function coefficients and correlation coefficients that facilitate the identification of suitable discriminants. Standardised discriminant function coefficients serve as multipliers when variables are normalised to a mean of 0 and a variance of 1. A coefficient nearer to 0 signifies a diminished influence on the discriminant function. Conversely, correlation coefficients measure the intensity of the association between dependent and independent variables. An elevated value indicates improved discriminatory capacity of the indicator.

6. An alternative approach to understanding discriminant analysis findings is clarifying each group according to its profile by employing the group means of the predictor variables. Generally, for every discriminant function, the group centroids signify the average discriminant scores for each group about the dependent variable. The centroids are arranged in a one-dimensional space, with one centre designated for each group. SPSS use the model constant to deliberately adjust centroid computations, establishing the weighted average of the centroid (weighted by the number of firms in each category) at 0.

7. The discriminant function is constructed with the unstandardised discriminant function coefficients.

8. The model's classification and discriminating capabilities are validated.

4. EMPIRICAL RESULTS

When developing a discriminant model based on multiple discriminant analysis, it was necessary to verify several fundamental assumptions (the significance level was set at 5 percent). Multiple discriminant analysis considered each debt indicator as an input variable, and the values of these variables were examined to determine whether they may be applied as significant determinants in the developed prediction models.

Since the classification of objects into groups of enterprises with and without significant financial difficulties due to corporate debt level can be predicted using group means as well as data from ANOVA results, it is necessary to determine if there are any significant differences between groups for any of the independent variables. Prospering and non-prospering enterprises have statistically significant differences in the means of particular debt indicators when the p-value is less than the chosen significance level. Conversely, if the groups of companies do not differ sufficiently, and it is not worthwhile to continue the investigation, according to the tests of equality of group means table (Table 2). Based on the results of the one-way analysis of variance, it is evident that in the conditions of the Visegrad Group countries, all debt indicators are considered statistical indicators for classifying enterprises into two groups, and all variables can be used as suitable discriminators, except for:

- X06, and X08 in Slovakia,
- X04, X05, X06, X07, X08, and X09 in Czechia
- X07, and X08 in Poland,
  X04, X06, X07, and X08 in Hungary.

Table 2

Test of equality of group means for Visegrad Group countries

Tests of Equality of Group Means								
	SK		**CZ**		**PL**		**HU**	
	Wilks' Lambda	Sig.	Wilks' Lambda	**Sig.**	**Wilks' Lambda**	**Sig.**	**Wilks' Lambda**	**Sig.**
X01_2021	0.941	0.000	0.939	0.000	0.960	0.000	0.968	0.000
X02_2021	0.914	0.000	0.944	0.000	0.958	0.000	0.964	0.000
X03_2021	0.955	0.000	0.953	0.000	0.975	0.000	0.961	0.000
X04_2021	0.998	0.001	0.999	0.179	0.995	0.000	0.999	0.320
X05_2021	0.972	0.000	0.999	0.211	0.981	0.000	0.980	0.000
X06_2021	1.000	0.313	0.999	0.296	0.998	0.011	0.997	0.066
X07_2021	0.997	0.000	0.999	0.280	0.999	0.153	0.999	0.254
X08_2021	1.000	0.103	1.000	0.450	1.000	0.323	1.000	0.668
X09_2021	0.983	0.000	0.999	0.182	0.993	0.000	0.990	0.000
X10_2021	0.965	0.000	0.980	0.000	0.982	0.000	0.983	0.000

Source: own elaboration.

In multiple discriminant analysis, a fundamental assumption is the equality of variance-covariance matrices within groups. Box's M tests the null hypothesis of the equality of these variance-covariance matrices, indicating that there is no difference in matrices among the dependent groups. However, this test must be statistically non-significant to retain the null hypothesis that there is no difference between the groups. The test results, summarized in Table 3, demonstrate that the variance-covariance matrices of each group have different log determinants, but generally, they should be equal.

Table 3

Log determinants table for Visegrad Group countries

Log Determinants			
SK	Y_2022	Rank	Log Determinant
	0	7	-9.448
	1	7	-12.648
	Pooled within-groups	7	-12.136
CZ	Y_2022	Rank	Log Determinant
	0	5	-6.594
	1	5	-6.428
	Pooled within-groups	5	-5.984
PL	Y_2022	Rank	Log Determinant
	0	7	-10.501
	1	7	-13.291
	Pooled within-groups	7	-12.848
HU	Y_2022	Rank	Log Determinant
	0	6	-19.090
	1	6	-13.225
	Pooled within-groups	6	-12.906
The ranks and natural logarithms of determinants printed are those of the group covariance matrices.			

Source: own elaboration.

The result of Box's M test (Table 4) of the equality of variance-covariance matrices indicates that the matrices cannot be considered equal. Nevertheless, in the case of a large sample, a high Box's M value is not considered too critical because, with a large sample, Box's M typically has a high value. The assumption of distinct variance-covariance matrices was used in subsequent SPSS calculations.

Table 4

Box's M test results table for Visegrad Group countries

Test Results			
SK	Box's M		2,291.701
	F	Approx.	81.040
		df1	28
		df2	643,695.700
		Sig.	0.000
CZ	Box's M		724.226
	F	Approx.	44.048
		df1	15
		df2	4,980.990
		Sig.	0.000
PL	Box's M		1,538.843
	F	Approx.	52.664
		df1	28
		df2	36,564.519
		Sig.	0.000
HU	Box's M		475.877
	F	Approx.	17.923
		df1	21
		df2	1,279.156
		Sig.	0.000
Tests null hypothesis of equal population covariance matrices.			

Source: own elaboration.

The information about each of the created discriminant functions is provided in the following part of the multiple discriminant analysis output, which can ascertain: (i) if there is statistical significance for the canonical discriminant function (p-value of Wilk's Lambda), and (ii) how strong is the canonical correlation. Canonical correlation, which provides an indicator of the overall model fit and is considered the amount of variance explained (R^2), expresses the correlation between groups of the dependent variable and the discriminant function. In Table 5, the result of canonical correlation is summarized alongside Wilk's Lambda, which is used to test the statistical significance of the discriminant function. Although the canonical correlation values for Slovakia (0.402), Poland (0.353), and Hungary (0.355) are relatively low, the models indicate statistically significant canonical correlations in the conditions of the Visegrad Group countries. Conversely, the Czech Republic (0.538) has the highest value among all the Visegrad Group countries and is considered to have a medium-strong canonical correlation.

Comparable to multiple regression, multiple discriminant analysis involves the interpretation of standardized coefficients of the canonical discriminant function. The standardized discriminant coefficients, whose structure indicates there is a relationship between the observed independent variable and the discriminant function, are the ones that are used to evaluate the relative classification significance of independent variables. The higher the value of the monitored coefficient, the stronger the relationship between the independent variable and the discriminant function. Standardized discriminant coefficients with values close to zero have a limited impact on the discriminant function, as demonstrated by Table 6. For two Visegrad Group countries, the best variable with the highest discriminative capability is the self-financing ratio (-1.506 for Slovakia; 1.701 for Poland). An exception is the Czech Republic, where the total indebtedness ratio (-1.828) is considered one of the most significant discriminators for classifying enterprises into those with or without financial difficulties. In Hungary, the current indebtedness ratio (1.904) is considered the variable with the highest discriminative capability. Slightly worse discriminators include the insolvency ratio (1.189) and the total indebtedness ratio (0.973) for Slovakia, the self-financing ratio (1.601) and the debt-to-equity ratio (1.400) for the Czech Republic, and the total indebtedness ratio (-1.493) and the insolvency ratio (-1.357) for Poland. In Hungary, the self-financing ratio (-1.845) and the insolvency ratio (1.664) are also considered relatively significant discriminators.

Table 5

Eigenvalues and Wilk's Lambda table for Visegrad Group countries

Eigenvalues					
	Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
SK	1	0.193	100.0	100.0	0.402
CZ	1	0.408	100.0	100.0	0.538
PL	1	0.142	100.0	100.0	0.353
HU	1	0.144	100.0	100.0	0.355
Wilk's Lambda					
	Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
SK	1	0.838	1,065.065	7	0.000
CZ	1	0.710	555.098	5	0.000
PL	1	0.876	281.801	7	0.000
HU	1	0.874	173.492	6	0.000

Source: own elaboration.

The correlation coefficient values among individual independent variables and the discriminant function are regarded as an alternate approach for indicating the relative importance of discriminators. When evaluating correlation coefficients, the self-financing ratio is considered the best discriminator in the conditions of Slovakia and Poland (-0.699 for Slovakia; 0.553 for Poland), and in the conditions of Hungary, the current indebtedness ratio (0.531) is particularly significant because these debt indicators achieve the strongest correlation with the discriminant function. In the Czech Republic, the total indebtedness ratio (-0.399) is considered one of the most significant indicators of financial prosperity for a firm. Other significant discriminators include the total indebtedness ratio (0.573) and current indebtedness ratio (0.496) for Slovakia and the self-financing ratio (0.383) and current indebtedness ratio (-0.353) for the Czech Republic. Although in the case of Slovakia and the Czech Republic, the current indebtedness ratio is considered the third indicator with the highest correlation coefficient, this debt indicator was not utilized in the resulting discriminant function. During the stepwise method, it was revealed that its contribution, even with the inclusion of other variables in the final model, is not sufficient. In the conditions of Poland, the total indebtedness ratio (-0.543) and current indebtedness ratio (-0.450) are considered other significant discriminators, and in Hungary, the self-financing ratio (-0.507) and total indebtedness (0.481) also have strong discriminatory capabilities. Although in the case of these Visegrad Group countries, certain debt indicators achieved a high correlation coefficient, the development of the discriminant model showed that the contribution of the current indebtedness ratio is not sufficient for both countries.

The discriminant score of the model for each business operating in the conditions of the Visegrad Group countries can be expressed through the unstandardized coefficients of the canonical discriminant function.

The prediction model of Slovakia

$$y_{SK} = -0{,}520 + 4{,}439X_1 - 8{,}107X_2 - 0{,}494X_4 - 0{,}594X_7 - 0{,}022X_8 - 0{,}116X_9 + 1{,}787X_{10} \quad (1)$$

The prediction model of Czechia

$$y_{CZ} = 0{,}388 - 9{,}048X_1 + 7{,}501X_2 + 1{,}367X_5 + 0{,}033X_8 - 1{,}151X_{10} \quad (2)$$

The prediction model of Poland

$$y_{PL} = -0{,}303 - 8{,}041X_1 + 9{,}409X_2 + 0{,}546X_5 + 1{,}216X_7 + 0{,}035X_8 + 0{,}306X_9 - 1{,}555X_{10} \quad (3)$$

The prediction model of Hungary

$$y_{HU} = -1{,}314 - 11{,}022X_2 + 10{,}372X_3 + 8{,}572X_4 - 0{,}872X_5 - 0{,}064X_8 + 2{,}530X_{10} \quad (4)$$

The discriminant function coefficients represent partial coefficients reflecting the involvement of each variable in the classification of groups of the dependent variable. In the conditions of the individual Visegrad Group countries, it can be observed that the same variables were used in developing the discriminant model but with different coefficients of the discriminant function. Subsequently, it was necessary to create a unique model used in the conditions of the Visegrad Group countries. Variables SK, CZ, and HU are categorical variables introduced into discriminant function analysis by means of dummy variables.

$$y_{V4} = -0{,}715 + 5{,}081X_1 - 7{,}221X_2 + 0{,}362X_3 - 0{,}096X_5 - 0{,}001X_6 - 0{,}783X_7 - 0{,}029X_8 - 0{,}089X_9 + 1{,}466X_{10} - 0{,}026SK - 0{,}006CZ - 0{,}088HU \quad (5)$$

Whether a firm belongs to the group of prosperous or non-prosperous enterprises can be determined by calculating the Z-Score individually for each company using unstandardized coefficients of the canonical discriminant function and subsequently comparing it with the centroids, the positions of which are detailed in Table 8. However, since SPSS uses a constant of the discriminant model in calculating centroids, a targeted correction is applied to ensure that the weighted mean of centroids equals 0. In this case, to assign a firm to one of the two considered groups, it is necessary to compare the Z-Score with zero because all resulting discriminant models in the conditions of the Visegrad Group countries include a constant. Therefore, comparing the Z-Score value with zero is sufficient. As the centroid value for a non-prosperous enterprise in the developed prediction model in the conditions of Slovakia, Hungary, and the complex model in the conditions of the Visegrad Group countries is a positive number, a non-prosperous firm is determined by a positive value, and a prosperous firm is determined by a negative value. Conversely, in the case of the created prediction models in the conditions of the Czech Republic and Poland, a non-prosperous enterprise is determined by a negative value, and a prosperous enterprise is determined by a positive value, as the centroid value for a non-prosperous one is negative.

Table 6

Function of group centroids for Visegrad Group countries

Function at Group Centroids					
	SK	CZ	PL	HU	V4
0	2,105	-5,452	-2,970	3,920	2,450
1	-0,092	0,075	0,048	-0,037	-0,068
Unstandardized canonical discriminant functions evaluated at group means					

Source: own elaboration.

However, for practical use of the discriminant model, it is essential to have sufficient discriminative capability. Based on the information from the classification table, it is evident that the created models have an overall discriminative capability higher than 88%, which is considered a very good classification. Developed models can be used to predict corporate bankruptcy in specific economic areas. In Slovakia, the model has a 68.7% classification ability for prosperous enterprises, but for predicting non-prosperous firms, the discriminant model achieves a classification ability of 89.5%, which is crucial in creating the bankruptcy prediction model. The developed model in Slovakia has a relatively high overall discriminant capability (88.6%). The discriminant capability of the Czech model is the best, as up to 98.1% of enterprises were correctly classified into one of the two considered groups. Based on the classification table, it is evident that the model for all firms operating in the Czech Republic has a 63.6% classification ability for prosperous enterprises. The model also exhibits excellent classification strength for enterprises facing financial difficulties, reaching 98.6%. In the case of Poland, the discriminant model achieves a 62.3% success rate in classifying prosperous enterprises. Conversely, the classification ability for non-prosperous enterprises is 96.4%, which is considered a very good classification ability. The constructed model in Poland also has a relatively excellent overall discriminant capability (95.9%). In Hungary, the model achieves a 50% classification ability for prosperous firms, which is the lowest level compared to other models created. However, the classification ability for enterprises facing financial difficulties reaches a level of 97.5%. The results from the classification table indicate that the developed discriminant model for Hungarian firms has a high overall classification ability (97.1%). The complex model used in the conditions of the Visegrad Group countries achieves an overall discriminant capability of 91.2%. From the classification table, it is evident that the model has a 65.4% classification ability for prosperous firms, but for predicting non-prosperous ones, the discriminant model

Developing new bankruptcy prediction models remains crucial because economic conditions and global events can have a significant impact on businesses. Models developed using historical data may not adequately capture the effects of unprecedented events or shifts in economic conditions. Continuous model development allows for adaptation to new economic realities. However, the business environment is dynamic and constantly evolving. New industries, technologies, and market trends emerge, affecting the financial health of companies. Bankruptcy prediction models need to adapt to these changes to remain relevant and effective. In summary, the ongoing importance of developing new bankruptcy prediction models lies in the need to adapt to a changing business environment, leverage advancements in data and technology, account for complex financial structures, and provide more accurate assessments of financial risk for effective decision-making.

5. DISCUSSION

The indebtedness indicators play a crucial role in revealing the financial health of an enterprise, contributing to its competitive position and stable development while eliminating potential financial difficulties. Despite numerous models developed using various financial ratios as predictors to achieve optimal outcomes, several authors argue that estimating bankruptcy risk remains challenging. Additionally, there is a considerable time gap in the creation of prediction models describing the business environment conditions in Visegrad Group countries (Valaskova et al., 2023).

In Slovakia, the initial scholars who were at the forefront of developing a predictive model using multiple discriminant analysis for agricultural firms were Chrastinova (1998) and Gurcik (2002). Chrastinova (1998) highlighted the significance of the total debt to total corporate assets ratio as a critical financial indicator for predicting corporate bankruptcy. This ratio, which aligns with the results of this paper, is one of the indicators incorporated into the developed model. Generally, the total indebtedness ratio is regarded as a significant predictor of bankruptcy. The model developed by Boda (2009) for Slovakia incorporates the self-financing ratio, a ratio highlighted by these authors as crucial, not only alongside earnings after taxes to total assets but also in conjunction with the current ratio. The self-financing ratio was included in the model by Hurtosova (2009), who was the first to employ logistic regression in the Slovak context for assessing future corporate prosperity, and the model created by Rohacova & Kral (2015) consists of seven indicators, with a specific emphasis on the self-financing ratio as the most significant debt ratio. Banyiova et al. (2014) utilized the Data Envelopment Analysis (DEA) approach in the bankruptcy prediction of Slovak agricultural companies. They suggested four models, each exhibiting relatively low overall accuracy ranging from 54% to 70%. Considering the earlier research, the authors inferred that more reliable predicting results could be achieved through models constructed using techniques such as linear multidimensional discriminant analysis, logit analysis, and classification trees. Kubicova & Faltus (2014) conducted intriguing research on a substantial sample of Slovak enterprises. They employed indicators related to income taxation for predicting corporate insolvency. However, the study revealed that individual indicators of this nature possess limited discriminatory capability. A logit model incorporating three taxation-related measures demonstrated superior prognostic results compared to single measures, but it fell short of ensuring higher efficiency than models incorporating various other financial indicators. Gulka (2016) proposed the Slovak logit model, incorporating not just the total indebtedness ratio and self-financing ratio but also the credit indebtedness ratio as indicators of indebtedness. Following this, Mihalovic (2016) established two prediction models in Slovakia based on discriminant analysis and logistic regression. The model, relying on five financial indicators, identified the current assets to total assets ratio as an ineffective discriminator between prosperous and non-prosperous enterprises. However, the other four financial indicators proved to be significant. According to the author's structural matrix, the current ratio emerged as the most effective negative separator, indicating that a higher current ratio value corresponded to a lower likelihood of enterprise failure. Kovacova & Kliestik (2017) employed logit and probit techniques to formulate bankruptcy prediction models for Slovak enterprises. The results suggested that the logit-based model slightly outperformed the probit-based model in terms of classification accuracy. Contributing to the theory and practice of Slovak corporate finance, Boda & Uradnicek (2019) critically assessed the efficiency of three prediction models for forecasting financial distress in Slovak agricultural firms. Among the three variables analysed, i.e. gross return on revenue, debt ratio, and days payables outstanding, proved crucial in predicting financial difficulty in the sample of Slovak enterprises.

Prediction models describing the Czech business environment through multiple discriminant analyses have been developed over distinct time periods. Considered pioneers in this field, the Neumaiers have created several models, each based on datasets from the manufacturing industry in the Czech Republic. The IN95 model (Neumaierova & Neumaier, 1995), crafted to address the specific Czech conditions at the time, achieved a 75% prediction success rate upon its compilation. Subsequent models, such as IN99, were created as indices more indicative of creditworthiness than bankruptcy. Modified versions of the IN01 and IN05 indexes, developed through discriminant analysis with fixed coefficients, followed without differentiation based on industry. These models capture the nuances of the Czech business environment and accounting legislation. Two significant debt ratios, namely the debt ratio and the interest coverage ratio, were observed in their models, which implies the best fit of the mentioned studies. Consequently, numerous research papers have emerged on this subject. Korab (2001) explored small and medium-sized business failures in the Czech Republic, employing fuzzy logic to evaluate the threat of corporate insolvency. Dvoracek & Sousedikova (2006) created a bankruptcy prediction model using univariate discriminant analysis. Dvoracek et al. (2008; 2012) utilized multidimensional linear discriminant analysis, logit analysis, and artificial neural networks to develop prediction models. The debt ratio and interest coverage ratio were included in the bankruptcy model by Jakubik & Teply (2011), who utilized logistic regression to develop a scoring model. Based on the coefficients of the indicators, these debt ratios appear to be the most crucial individual indicators of business failure because it is evident that a higher debt ratio increases the probability of default, whereas a higher ability to repay debt reduces this probability. The authors demonstrated the use of conventional techniques to assess the financial health of the corporate sector, employing logistic regression to establish a scoring model based on seven variables. Generally, the resulting JT index serves as a comprehensive measure of the creditworthiness of the Czech corporate sector. Pitrova (2011) applied Altman's model to examine multicollinearity between indicators and the impact of individual variables on the discriminant score of enterprises. Hampel et al. (2012) introduced a predictive model designed to anticipate the financial insolvency of companies within the Czech agribusiness sector. Notably, they employed a production function, an uncommon approach in this field of study, and the outcomes were subsequently juxtaposed with findings derived from the Altman model. While the two models exhibited comparable effectiveness, it is crucial to acknowledge the limitations inherent in the research, namely the small sample size, which renders the drawn conclusions somewhat inconclusive. The interest coverage ratio was considered a significant debt indicator by Kalouda & Vanicek (2013), who proposed two national bankruptcy prediction models, CZ2 and FLKp, based on linear multidimensional discriminant analysis. Kocmanova et al. (2014) created a prediction model for sustainable development in manufacturing enterprises. Machek et al. (2015) focused on creating a model using linear discriminant analysis and logit analysis for enterprises in the cultural sector. Bems et al. (2015) introduced a novel scoring method for predicting corporate bankruptcy. This innovative approach is grounded in a modified magic square, originally designed for assessing the economic performance of a country. By utilizing financial ratios extracted from the financial statements of the firm and incorporating data related to the corporate default, the method provides a visual depiction of the company's score. This graphical illustration, presented a diagram, provides a straightforward visualization of each factor's contribution to the overall score. The resulting model to predict the survival of transportation and shipping companies by Vochozka et al. (2015) incorporated both current and non-current indebtedness ratios. Klepac & Hampl (2018) focused on forecasting the bankruptcy of 1,000 medium-sized enterprises in the EU, of which 170 companies experienced bankruptcy in 2014, considering the lag of the utilized features. To optimize their predictions, the authors explored various classification models, ultimately selecting the support vector machine method with spline as well as decision trees, random forests, and adaptive boosting. They concluded that the chosen attributes for analysis included return on assets, while from debt indicators, primarily interest coverage ratio and insolvency ratio were used. Among the indicators of indebtedness, the pivotal variables employed in the classification models by Stankova & Hampl (2018) for each respective year predominantly include the total indebtedness ratio and the insolvency ratio. To facilitate classification, the authors opted for the fundamental statistical approach of logistic regression, alongside a representative machine learning method, specifically support vector machines and classification trees, to formulate models for predicting bankruptcy.

In the middle of the 1990s, significant advancements in predicting corporate bankruptcy emerged in Poland. Initially, researchers sought to forecast enterprise bankruptcies by adopting foreign models, as stated by Maczynska (1994). Due to limited data accessibility, the modelling process involved ratio analysis, followed by multivariate linear discriminant analysis (Kniewski, 2004). Hamrol et al. (2004) introduced the Poznanski model, achieving a remarkable 96% classification and prediction accuracy. Numerous models employing discriminant analysis were subsequently developed in the Polish business context, with larger sample sizes, as evidenced by Korol (2004) or Prusak (2005). Gruszczynski (2003) conducted comprehensive research as well. Employing an expert method, the author chose 23 firms with favorable financial standing and another 23 with poor financial conditions. The learning sample was utilized to construct binomial logit models. Among the debt indicators, the ratio of total liabilities to total corporate assets proved to be statistically significant. In this context, it's important to highlight that the logit model developed by Stepien & Strak (2004) was employed to construct the rating, incorporating the debt ratio among the financial indicators as predictors. Wedzki (2005) introduced several logit models for bankruptcy in the Polish economy, including a multi-branch model for industrial enterprises. In the created predictive models from debt indicators, not only the most significant ratio of total liabilities to total corporate assets was included, but also the interest coverage ratio and leverage index. In comparison to other countries, logistic regression began to be used in the prediction models development in the years that followed. Logit models, incorporating various economic and financial indicators, were employed to forecast the probability of default. Holda (2006) was among the researchers who pioneered the development of the first logit models in the Polish context. The resulting bankruptcy prediction model consisted of three key predictors, among which the debt ratio can be classified as one of the debt indicators. Maslanka (2008), who developed a prediction model two years later, utilized linear discriminant analysis in the model development. The result was a discriminant function consisting of six key predictors. In this case, among the debt indicators, the model included not only the self-financing ratio but also the non-current asset coverage ratio, a variable seldom used in the development of the bankruptcy prediction model in the past. Pisula et al. (2013) concentrated on identifying factors that describe the risk of enterprise bankruptcy in terms of their effectiveness in predicting outcomes over one- and two-year horizons. They applied logistic regression models, classification trees, and two artificial neural networks. The primary tool employed to assess the effectiveness of model classification in this case was the correct classification matrices. Similar to their previous study, Pisula et al. (2015) updated their research, choosing 28 financial indicators characterizing the financial condition and managerial effectiveness of the monitored enterprises as bankruptcy predictors. In addition to the total debt ratio, they incorporated current and non-current indebtedness ratios, the debt-to-equity ratio, and considered the financial leverage ratio as a significant predictor of bankruptcy. Brozyna et al. (2016) also utilized the same debt indicators in their study. They focused on providing validation values for the described models in predicting potential bankruptcy signals and assessing the financial condition of entities in the transport and logistics sectors in both Poland and Slovakia.

In Hungary, the concern over corporate insolvency in the early 1990s led to numerous publications focusing on bankruptcy prediction models. The pioneering work by Hajdu & Virag (2001) marked the inception of this research, utilizing multidimensional discriminant analysis and financial data from 10,000 economic units. The authors developed 41 bankruptcy models, encompassing one for the national economy, ten for specific economic sectors, and thirty for various branches. Notably, all developed models demonstrated a classification accuracy exceeding 90%. The subsequent model by Virag & Kristof (2005) involved artificial neural networks, yielding a distinct model with enhanced efficiency compared to the initial Hungarian bankruptcy model. Using the same learning sample from the previous studies, Virag & Nyitrai (2013) employed support vector machines and rough set theory, similar to artificial neural networks, achieving comparable results. Szeverin & Laszlo (2014) extended the scope to predict the failure of Hungarian small and medium-sized enterprises. Their approach included linear discriminant analysis, logit analysis, classification trees, and artificial neural networks, with a comparative assessment of classification abilities against other Hungarian and foreign models. The Hungarian business environment witnessed the development of several sector-specific models, such as the model for dairy firms by Rozsa (2014), the model for meat processing enterprises by Peto & Rozsa (2015), and the model for commercial enterprises by Dorgai et al. (2016). Bauer & Edresz (2016) utilized a panel probit model to calculate the probability of bankruptcy, incorporating not only conventional firm-level performance indicators but also additional information on firm size, age, ownership, export status, industry, and macro variables. Upon reviewing the collective studies on this issue, it is apparent that Hungary lags behind other Visegrad Group countries in the development of bankruptcy prediction models.

The development of new bankruptcy prediction models has become an essential part of the business environment, even after the COVID-19 pandemic. The pandemic has brought significant changes to the business environment, presenting new challenges for enterprises and economies (David & Dadkhah, 2023).

Therefore, it is necessary to update existing bankruptcy models to account for these new conditions (Papik et al., 2023). As mentioned by Blazek et al. (2023), the pandemic witnessed unexpected events and rapid changes. Bankruptcy models should be capable of incorporating uncertainty and flexibly responding to rapid changes, which is crucial in an unstable environment. According to Jones (2023), continually creating new prediction models is important for optimizing predictive power because models developed before the pandemic may not deliver optimal results in new conditions. Updating and optimizing existing models can enhance their predictive power and their ability to identify bankruptcy risks. Since bankruptcy models are vital tools for managers, investors, and other stakeholders in decision-making, Rahman et al. (2023) states that updated models can provide current and reliable information about the financial stability of firms. In general, analysing the performance of existing models during the pandemic can offer valuable insights into their effectiveness in times of crisis. These experiences can help improve future bankruptcy models and provide a better understanding of how crises impact the financial stability of enterprises (Vojtkova & Mihalech, 2023).

The COVID-19 pandemic has significantly impacted businesses and the economy not only globally but also in the conditions of the Visegrad Group countries. This impact is evident even in the development of bankruptcy prediction models. The pandemic has caused substantial economic turbulence that was challenging to forecast. Many existing bankruptcy models did not encompass pandemic scenarios, rendering them limited in predictions and explanations (Matejic et al., 2022). Given the rapid changes in the business environment, it was necessary to regularly update existing bankruptcy models. Traditional models, relying on long-term trends and stable conditions, may be less effective in short-term and turbulent situations (Boratynska, 2021), which underlines the importance of research outputs. Papik & Papikova (2023) conducted an analysis of how the crisis affected the efficacy of bankruptcy prediction models. The authors developed prediction models for two non-crisis periods and one crisis period, while their results revealed a notable decline in the performance of prediction models during crisis periods compared to non-crisis periods. According to Sarhadi et al. (2022), the weaker performance is attributed to reduced sensitivity levels, indicating that bankruptcies during crises were likely unexpected outcomes linked to the crisis. Durana & Valaskova (2022) investigated the striking effect of Industry 4.0 on earnings during the crisis in the Visegrad Group countries. The authors focused on small and medium-sized enterprises and their profits from using smart sensors and concluded that the COVID-19 pandemic caused collapses and defects for very large enterprises and large enterprises, especially for small and medium-sized enterprises, because it has been proven that earnings volatility or a rapid decrease in earnings may lead to bankruptcy. Blazek et al. (2023) focused on the conduct of businesses in the Visegrad Group countries during crises, particularly exploring shifts in enterprise behavior amid the pandemic. Their results indicated that the COVID-19 pandemic instigated a pattern of business transition from one stage to another. Consequently, it is evident that the pandemic brought about significant alterations. Manipulation of earnings can manifest in various ways, including altering data from its true state to a form desired by enterprises, distorting actual income and assets, withholding accurate information about corporate finances, or exploiting legal loopholes to elevate the enterprise's position in the overall benchmark. In essence, there was a necessity to ensure the longevity of corporate finances and avoid bankruptcy. The transformations induced by COVID-19 in market economies have heightened the significance of evaluating the financial health of companies and sectors. It is imperative for managers, lenders, and investors to accurately assess the financial well-being of companies. Therefore, the selection of indicators that illustrate variations in market sector values before and during the COVID-19 pandemic is of utmost importance. In the study conducted by Tomczak (2021), which incorporated quarterly and annual analyses spanning from 2017 to 2021, 82 indicators were considered. The sample comprised publicly listed companies in six sectors within the Visegrad Group: manufacturing, construction, retail, wholesale trade, transportation and warehousing, and energy. The author concluded that, among debt indicators, total debt and equity leverage emerge as the most critical ratios. Valaskova et al. (2023) developed a bankruptcy prediction model using financial data from enterprises spanning all sectors in the Visegrad Group countries during the post-pandemic period (2020-2021). The aim was to identify key predictors of bankruptcy. Multiple models, incorporating 6-14 financial indicators, were created using various combinations of predictors and coefficients. Across all Visegrad Group countries, the total indebtedness ratio emerged as the most effective variable with superior discriminating power, consistently included in each developed model. These findings hold relevance for other Central European nations with economic development patterns akin to those examined in the study.

In general, the COVID-19 pandemic has led to a greater need for flexibility and adaptability in the development of bankruptcy prediction models. Models should be capable of incorporating uncertainty, rapid changes, and unexpected events to be truly effective in supporting decision-making in an uncertain environment.

6. CONCLUSION

Apart from reviewing historical events, financial analysis aims to forecast the corporate financial health, and this information is of primary interest to the creditors of the enterprise. Individual indicators cannot reliably anticipate the development of financial health. This challenge is specifically addressed by prediction models, which typically emphasize the identification of a singular coefficient to categorize the enterprise into predefined groups. While consolidating the outcome of financial analysis into a single composite indicator is appealing, these models still fall short of encompassing all the intricacies of enterprises, making their applicability not universally comprehensive.

The main aim of this paper was to construct a bankruptcy prediction model utilizing financial data from 12,816 enterprises operating within the Visegrad Group countries and to anticipate financial well-being in the post-pandemic period, thereby mitigating potential risks for all involved parties. Employing multiple discriminant analyses, distinct prediction models were formulated for each Visegrad Group country, along with a complex model for the Visegrad Group, while relevant financial indicators were employed as predictors. The developed models, consisting of five to seven indicators, were not only based on varied predictor combinations but also incorporated different coefficients. In two Visegrad Group countries, the self-financing ratio emerged as the best variable with the highest discriminative capability. Except for the Czech Republic, a notable exception arises, as the total indebtedness ratio is deemed one of the most crucial discriminators for classifying enterprises into those facing or avoiding financial difficulties. The current indebtedness ratio has been determined as the variable with the highest discriminative capability in Hungary. The insolvency ratio and total indebtedness ratio are slightly worse discriminators in Slovakia, whereas the self-financing ratio and debt-to-equity ratio are significant discriminators in the Czech Republic. For Poland, the total indebtedness ratio and insolvency ratio are considered relatively significant discriminators. In Hungary, both the self-financing and the insolvency ratio are predictors with the appropriate discriminative capability. Generally, for practical application, it is imperative that the model possess sufficient discriminative abilities. The research results indicate that the developed models exhibit an overall discriminant ability exceeding 88%.

While this paper adds value to the existing literature and holds practical implications for future financial stability and the development of the enterprise, it is crucial to acknowledge a particular limitation. The study is constrained by the fact that the results of the multiple discriminant analysis may not be as widely acknowledged as those obtained through alternative methods, such as logistic regression or neural networks. Future research should be conducted to identify which method provides more accurate and precise outputs when predicting corporate financial health.

ACKNOWLEDGEMENT

This research was financially supported by the Slovak Research and Development Agency Grant VEGA 1/0494/24: Metamorphoses and causalities of indebtedness, liquidity and solvency of companies in the context of the global environment and faculty institutional research 1/KE/2023: The use of quantitative methods to assess the impact of the latest crisis on the performance of business entities in V4 countries at the Faculty of Operation and Economics of Transport and Communications, University of Zilina, Slovakia.

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