Ekonomicko-manazerske spektrum
2025, Volume 19, Issue 1, pp. 83-96

EVALUATING FINANCIAL STABILITY AND PREDICTIVE MODELLING OF SME PROSPERITY IN MANUFACTURING

Veronika Kusnierikova[1,a], Simona Vojtekova[1,b,*] and Sheshadri Chatterjee[2,c]

[1] Department of Economics, Faculty of Operation and Economics of Transport and Communications, University of Zilina, Univerzitna 1, 010 26 Zilina, Slovakia
[2]Department of Management, Indian Institute of Information Technology, Lucknow, 226002, India
[a]kusnierikova3@stud.uniza.sk,
[b]simona.vojtekova@stud.uniza.sk,
[c]sheshadri.academic@gmail.com
[*]Corresponding author

Cite as: *Kusnierikova, V., Vojtekova, S., Chatterjee, S. (2025). Evaluating financial stability and predictive modelling of SME prosperity in manufacturing, Ekonomicko-manazerske spektrum, 19(1), 83-96.*

Available at: *dx.doi.org/10.26552/ems.2025.1.83-96*

Received: 7 February 2025; Received in revised form: 30 April 2025; Accepted: 30 May 2025; Available online: 30 June 2025

Abstract:
Research background: This study evaluates the financial stability of small and medium-sized enterprises (SMEs) within Slovak manufacturing, classified under NACE C. The sector, which is characterised by the physical or chemical transformation of materials into new products, represents a significant part of the Slovak economy. The analysis uses financial data from the FinStat database covering the period 2018–2023, focusing on key financial ratios related to activity, liquidity, profitability, and indebtedness.
Purpose of the article: The main aim of this paper is to assess the financial health of SMEs in Slovak manufacturing and to develop a predictive model that identifies financially distressed firms using key financial ratios.
Methods: A sample of 1,848 firms continuously observed over six years was analysed to assess temporal changes in financial performance indicators using median values. Statistical significance was tested via the non-parametric Friedman test, revealing that all selected financial ratios were influenced by time. Indicators such as assets turnover, cash ratio, return on equity, and indebtedness ratios demonstrated notable fluctuations, reflecting shifts in firms' operational and financial health. Furthermore, the study developed a predictive model for financial health in 2023 based on 2022 financial indicators through discriminant analysis. The model classified firms as prosperous or non-prosperous based on the equity-to-liabilities ratio.
Findings & Value added: Key predictors included the self-financing ratio, financial leverage, commercial insolvency ratio, current ratio, return on equity, and creditors' payment period. The model achieved a high classification accuracy of 91.2%, correctly identifying 96.1% of prosperous and 86.3% of non-prosperous enterprises. The model's excellent predictive capability was further confirmed by the ROC curve analysis, yielding an area under the curve (AUC) of 0.952. These results highlight the model's effectiveness in forecasting financial health for manufacturing SMEs in the post-COVID context in Slovakia.

Keywords: corporate finance; financial health; NACE C; prediction model; SMEs

JEL Classification: G17; G33; L60

1. Introduction

Financial analysis is a fundamental component of corporate financial management. A crucial element of financial analysis is utilising previous data on a company's performance to predict its future economic growth (Jencova et al., 2021). Financial and economic analysis functions as a feedback mechanism that enables a corporation to assess the effectiveness of its decisions, regardless of whether they fulfilled initial expectations (Podhorska and Siekelova, 2020).

The assessment of a company's financial health is a complex endeavour that necessitates an emphasis on liquidity, activity, indebtedness, and profitability, each offering distinct perspectives on the company's capacity to fulfil its obligations, the efficiency of asset utilisation, the composition of financial resources, and overall performance. Improved financial health is associated with enhanced financial success and vice versa (Das et al., 2024).

The study examines activity, liquidity, debt, and profitability. The rationale for employing four distinct types of indicators is that a single indicator is inadequate for evaluating a company's financial health and performance (Jihadi et al., 2021). Activity indicators reflect the efficacy of management about a company's assets, often representing the capital invested in assets/liabilities, asset turnover, or turnover period. Effective corporate management is essential for minimising expenses and establishing conditions conducive to profit generation. Efficiency is a fundamental criterion for evaluating a company's financial health. The method of asset management significantly influences both growth and the reduction of profit. It also elucidates the positioning of enterprises within a competitive market landscape (Durana et al., 2025).

Liquidity analysis provides results that indicate a company's capacity to fulfil its obligations punctually. A financially sound corporation can meet its obligations, but a company in financial distress encounters challenges in doing so. Consequently, it is essential to sustain the company's liquidity at an appropriate level. To maintain perpetual solvency, or liquidity, a corporation must consistently analyse, monitor, and assess its liquidity (Stangova and Vighova, 2021).

From the owner's perspective, profitability indicators are regarded as the most significant ratio metrics. Profitability indicators serve to assess the outcomes of company endeavours (Bugaj et al., 2023).

Debt analysis involves monitoring the ratio of equity to debt inside a corporation, which affects financial stability and the profitability of stock. An increased equity ratio establishes the conditions for enhanced financial independence and stability of the organisation. Utilising debt may enhance the profitability of equities via financial leverage. Elevated debt levels augment the cost of borrowing, resulting in corporate instability and the onset of liquidity issues, as interest obligations on loan capital must also be fulfilled. Monitoring debt is a crucial aspect of a firm's financial success, particularly when the company lacks sufficient equity. Nonetheless, escalating debt might provide a challenging financial predicament for a corporation, manifesting as insolvency and an incapacity to meet its forthcoming obligations (Culkova et al., 2018; Valaskova et al., 2021; Gajdosikova et al., 2023).

The number of financial performance indicators of a company is almost infinite, so it is necessary to select those that best serve the purpose of the analysis (Durana et al., 2024; Kumar et al., 2022). In assessing a company's financial health, we utilise terminology such as failure, insolvency, and bankruptcy. Currently, we have a contradiction in the interpretation of these words at both economic and legal levels, and there is also discord in the professional literature over their meanings (Kliestik et al., 2019).

The initial research on forecasting corporate insolvency was published in the early 20th century (Valaskova et al., 2023). The obstacle of forecasting a company's financial situation, namely the risk of financial distress, is crucial not only for management to implement necessary actions but also for all stakeholders to understand the company's financial health and potential future status. Presently, there exist several hundred to thousands of predictive models developed at times, utilising certain samples, and under distinct economic situations. This advancement is always evolving and gaining traction owing to advancements in computer technology (Pavlicko et al., 2021).

In the contemporary economy, securing the financial stability of an organisation and enhancing its competitiveness is notably challenging. Researchers must use old and contemporary measurements to assess the economic sustainability of firms. Assessing the financial status of an organisation and forecasting its future trajectory is essential. Consequently, the pursuit of effective models for forecasting bankruptcy is crucial not only in academic research but also in the operations of corporate organisations (Jencova et al., 2024).

Once more, while categorising methodologies for forecasting the financial stability of corporations, we observe several classifications from many authors. Kliestik et al. (2019) categorise methodologies or models into the following: univariate models, multiple discriminant analysis, linear probability models, LOGIT and PROBIT models, decision trees, survival analysis, expert systems, mathematical programming, neural networks, genetic algorithms and fuzzy sets.

Small and medium-sized enterprises represent a fundamental pillar of the modern economy, whose importance goes beyond their individual dimensions and aggregates into macroeconomic benefits. SMEs play a multifaceted role, primarily manifesting in four key dimensions. They are the primary generator of employment and a catalyst for social cohesion, while in many economies they constitute most enterprises and absorb a significant share of the workforce. This phenomenon has a direct impact on unemployment rates and income distribution, thereby contributing to the stabilization of society and the reduction of social disparities (Chatterjee et al., 2022b). At the same time, they represent a dynamic source of innovation and technological progress. Thanks to their flexibility, agility and often less rigid organizational structure, SMEs can respond more quickly to market stimuli and implement new ideas (Chatterjee et al., 2022a). This incubation capacity for innovation is critical to sustaining the competitiveness of national economies at the global level (Chatterjee et al., 2023a). In addition, SMEs strengthen local and regional economic resilience. Their anchoring in local communities leads to the reinvestment of capital in each geographical area and to the strengthening of local supply-demand chains. This decentralized economic model contributes to the diversification of risk and the reduction of dependence on a few large corporations, thereby increasing the overall robustness of the economy (Chatterjee et al., 2021). Finally, they are an essential element for the structural adaptability of the economy. In the context of dynamically changing market conditions and unexpected external shocks, the ability of SMEs to quickly adapt to new challenges is invaluable (Chatterjee et al., 2023b). Their ability to transform their business models and respond to shifts in demand allows the economy to navigate through crises more effectively and ensure sustainable development (Chaudhuri et al., 2022).

That is why it is necessary to map the financial health of SMEs in each sector, especially in those with a significant share in the economy. The goal of this article is to assess the financial health of SMEs in Slovak manufacturing and to develop a predictive model that identifies financially distressed firms using key financial ratios.

The article is structured as follows: The introduction focuses on research incentives and the significance of SMEs. Methodology describes the used indicators, analysed period and methods run to detect the impact of the time and to create a prediction model. Results show specific median values for individual indicators and significant indicators within the classification of prosperous and non-prosperous enterprises. Discussion compared the results of the similar investigations. The conclusions sum up the limitations and future ways to explore.

2. Methodology

The study encompasses an evaluation of the financial stability of small and medium-sized firms within the chosen sector. The chosen sector is derived from the statistical classification of economic activities, it is NACE C, which denotes manufacturing. This area encompasses the physical or chemical alteration of materials, substances, or components into novel products. This segment is the most prominent and advanced within the context of economic activity in Slovakia, which is the reason for its selection by us (SK NACE, 2025).

The input data is derived from the financial statements of companies acquired from the FinStat database. These are small and medium-sized firms classified under NACE C. The quantity of firms has fluctuated in certain years (Table 1). These enterprises were used to compute median values of indicators.

Table 1: Sample of enterprises

years	2018	2019	2020	2021	2022	2023
Number of business entities in NACE C	2,844	2,879	2,798	2,798	2,857	2,761

Source: own elaboration

During the observed period, it can be asserted that there were minor fluctuations in the number of firms under NACE C. The fluctuations in the number of firms may be attributed to the formation of new entities and the dissolution of existing ones within specific sectors.

$$\text{Assets turnover} = \frac{\text{sales}}{\text{average assets}} \tag{1}$$

$$\text{Assets turnover period} = \frac{\text{average assets}}{\text{sales}} \cdot 365 \tag{2}$$

$$\text{Inventory turnover} = \frac{\text{sales}}{\text{average inventory}} \tag{3}$$

$$\text{Inventory turnover period} = \frac{\text{average invntory}}{\text{sales}} \cdot 365 \tag{4}$$

$$\text{Collection period ratio} = \frac{\text{average receivables}}{\text{sales}} \cdot 365 \tag{5}$$

$$\text{Credit period ratio} = \frac{\text{average liabilities}}{\text{operating costs}} \cdot 365 \tag{6}$$

$$\text{Cash ratio} = \frac{\text{cash and equivalents}}{\text{short term liabilities}} \tag{7}$$

$$\text{Quick ratio} = \frac{\text{cash and equivalents} + \text{short term receivables}}{\text{short term liabilities}} \tag{8}$$

$$\text{Current ratio} = \frac{\text{cash and equivalents} + \text{short term receivables} + \text{inventory}}{\text{short term liabilities}} \quad (9)$$

$$\text{Return on equity} = \frac{\text{EAT}}{\text{equity}} \cdot 100 \quad (10)$$

$$\text{Return on assets} = \frac{\text{EAT}}{\text{total assets}} \cdot 100 \quad (11)$$

$$\text{Return on sales} = \frac{\text{EAT}}{\text{sales}} \cdot 100 \quad (12)$$

$$\text{Total indebtedness ratio} = \frac{\text{total liabilities}}{\text{total assets}} \cdot 100 \quad (13)$$

$$\text{Self financing ratio} = \frac{\text{equity}}{\text{total assets}} \cdot 100 \quad (14)$$

$$\text{Long term indebtedness ratio} = \frac{\text{long term liabilities}}{\text{total assets}} \cdot 100 \quad (15)$$

$$\text{Short term indebtedness ratio} = \frac{\text{short term liabilities}}{\text{total assets}} \cdot 100 \quad (16)$$

$$\text{Financial leverage ratio} = \frac{\text{total assets}}{\text{equity}} \quad (17)$$

$$\text{Commercial insolvency ratio} = \frac{\text{commercial liabilities}}{\text{commercial receivables}} \quad (18)$$

$$\text{Total insolvency ratio} = \frac{\text{short term liabilities}}{\text{short term receivables}} \quad (19)$$

$$\text{Interest coverage ratio} = \frac{\text{EBIT} + \text{interest paid}}{\text{interest paid}} \quad (20)$$

The study examines the examination of ratio indicators and the impact of time on their value. In the analysed period from 2018 to 2023, chosen indicators of activity, liquidity, profitability, and indebtedness for NACE C were examined among the ratio indicators. The examination of indicators, their developmental comparison, and subsequent interpretation are conducted based on the computed median values for the specified segment.

The examination of the time influence on the value of ratio indicators utilises the computed values from the sample set, especially the values of 1848 firms that were included in the sample sets for the full monitored period from 2018 to 2023. The significance level for the subsequent statistical tests is set at $\alpha = 0.05$. The computations are executed with the IBM SPSS Statistics 26 software. In the event of a breach of the assumptions of normal distribution, independence of samples, and homoscedasticity, one may employ a non-parametric ANOVA test for dependent samples, known as the Friedman test.

Development of the hypotheses for the Friedman test:

$\mathrm{H_0}$: The distribution of values remains consistent over all years. The value of the chosen indicators is unaffected by time.
$\mathrm{H_1}$: A minimum of two distributions exhibits positional differences. Time influences the valuation of the chosen metrics.

Discriminant analysis assesses whether the categorisation of a dependent variable (Y) is influenced by at least one independent variable (X). Utilising data from 2022, financial health in 2023 was forecasted by discriminant analysis and the stepwise technique. The independent variables consist of 20 indicators that were analysed and computed for the year 2022. The dependent variable is prosperity, as assessed inside a company in crisis in 2023.

A company in crisis is based on Slovak legislation according to Act 513/1991 Coll—Commercial Code. If the equity to liabilities ratio is more than or equal to 0.08, the firm is prosperous. In the second scenario, if the value of the specified ratio is below 0.08, the firm is deemed unprosperous.

$$\text{prosperity} = \frac{\text{equity}}{\text{liabilities}} \tag{21}$$

Out of a total of 2,478 enterprises, 102 are classified as non-prosperous, while 2,376 are deemed prosperous based on prosperity calculations. We used these 2,478 enterprises because we could identify their business activity in both 2022 and 2023. Finally, a total of 204 firms, including 102 non-prosperous and 102 randomly selected prosperous enterprises, were used to develop the classification equation in the SPSS software.

3. Results

Firstly, to evaluate how selected financial indicators evolved over time, median values of key ratios related to activity, liquidity, profitability, and indebtedness were calculated for each year between 2018 and 2023. The Friedman test was applied to determine whether time had a statistically significant impact on the indicators' values. The following Table 2 presents the calculated medians alongside the computed median values of financial analysis ratios for NACE C with the outcomes of the Friedman test. Upon comparing the estimated p-values with the significance threshold α for all indicators, the null hypothesis $\mathrm{H_0}$ is rejected, since the p-values for all indicators were below 0.001, hence supporting the acceptance of the alternative hypothesis $\mathrm{H_1}$. Upon doing the test, we concluded that a minimum of two distributions vary in position for each indicator, indicating that time influences the value of all selected indicators.

Secondly, we ran the procedures to create a prediction model for SMEs in the manufacturing sector. The assumptions related to the application of discriminant analysis were validated. These represent the disparities in the mean values of the independent variables and the concordance of the covariance matrices. Upon comparing the p-values from Table 3 with the significance threshold of 0.05, the subsequent conclusion was reached. The null hypothesis is rejected, and the alternative hypothesis is accepted. This outcome delineates the varying mean values of the independent variables and confirms the premise of their adequate discriminatory ability.

In developing a predictive model, it is essential to utilise Box's test for the equality of covariance matrices. Upon comparing the p-value from Table 4 with the significance level of 0.05, the conclusion drawn is that the null hypothesis is rejected and the alternative hypothesis is accepted, indicating that the covariance matrices of the independent variables between the group of prosperous enterprises and the group of non-prosperous enterprises are not identical. Consequently, two distinct covariance matrices were employed in subsequent calculations.

Table 5 presents the computed values of the variance inflation factor (VIF) for each independent variable. All VIF values are below 2.5, indicating an absence of substantial linear dependency among the explanatory variables. This computation demonstrates the absence of multicollinearity.

Table 2: Values of calculated indicators and result of analysing the impact of time on indicators

	2018	2019	2020	2021	2022	2023	Impact of time
Activity							
Assets turnover	1.56	1.55	1.43	1.45	1.60	1.55	< 0.001
Assets turnover period	233.76	234.79	256.10	250.87	228.30	235.48	
Inventory turnover	7.41	7.32	6.72	6.06	6.74	7.00	
Inventory turnover period	49.27	49.82	54.33	60.22	54.14	52.11	
Collection period ratio	43.10	39.34	39.36	42.13	39.28	38.56	
Credit period ratio	52.41	48.52	48.52	51.79	47.57	43.89	
Liquidity							
Cash ratio	0.13	0.15	0.20	0.18	0.16	0.19	< 0.001
Quick ratio	0.80	0.81	0.89	0.87	0.84	0.95	
Current ratio	1.24	1.26	1.36	1.38	1.39	1.46	
Profitability							
Return on equity	7.57%	6.61%	6.34%	8.42%	8.82%	9.24%	< 0.001
Return on assets	2.59%	2.38%	2.58%	3.30%	3.38%	3.60%	
Return on sales	1.68%	1.54%	1.80%	2.14%	2.16%	2.32%	
Indebtedness							
Total indebtedness ratio	64.13%	62.75%	60.82%	60.90%	60.30%	58.48%	< 0.001
Self-financing ratio	35.87%	37.25%	39.18%	39.10%	39.70%	41.52%	
Long-term indebtedness ratio	1.82%	2.01%	1.90%	1.91%	1.77%	1.79%	
Short-term indebtedness ratio	32.76%	30.71%	28.66%	30.01%	30.60%	27.77%	
Financial leverage ratio	2.42	2.36	2.24	2.31	2.31	2.19	
Commercial insolvency ratio	0.86	0.86	0.85	0.86	0.87	0.79	
Total insolvency ratio	1.35	1.41	1.40	1.36	1.38	1.23	
Interest coverage ratio	3.39	3.14	2.91	4.47	4.62	3.43	

Source: own elaboration based on calculations and output from IBM SPSS

Table 3: Tests of equality of group means

Indicator	Wilks' lambda	F-statistics	df1	df2	*p*-value
Self-financing ratio	0.637	114.888	1	202	< 0.001
Financial leverage ratio	0.945	11.832	1	202	0.001
Insolvency ratio	0.953	9.997	1	202	0.002
Current ratio	0.866	31.324	1	202	< 0.001
Return on equity	0.864	31.831	1	202	< 0.001
Credit period ratio	0.890	24.904	1	202	< 0.001

Source: own elaboration based on output from IBM SPSS

Table 4: Box's test of equality of covariance matrices

Box's M		1,186.911
F	Approx.	54.733
	df1	21
	df2	150,077.05
	p-value	< 0.001

Source: own elaboration based on output from IBM SPSS

Table 5: Variance inflation factor

Financial indicator	VIF
Self-financing ratio	1.489
Financial leverage ratio	1.070
Insolvency ratio	1.050
Current ratio	1.401
Return on equity	1.038

Credit period ratio	1.168

Source: own elaboration based on output from IBM SPSS

Table 6 presents two values: the eigenvalue and the canonical correlation value of the established classification function from the canonical discriminant analysis. The number 0.744 signifies that the canonical discriminant function can effectively differentiate between prosperous and unprosperous firms with a high degree of accuracy.

Table 6: Canonical correlation of the discriminant function

Function	Eigenvalue	Canonical correlation
1	1.243	0.744

Source: own elaboration based on output from IBM SPSS

Table 7 presents the value of Wilks' lambda, utilised to assess the relevance of the established discriminant function. Upon comparing the p-value to the significance level of 0.05, the null hypothesis is rejected, and the alternative hypothesis is accepted. This outcome indicates that the established canonical discriminant function is statistically significant.

Table 7: Significance of the canonical discriminant function

Test of functions	Wilks' lambda	Chi-square	df	*p*-value
1	0.446	160.743	6	< 0.001

Source: own elaboration based on output from IBM SPSS

Table 8 facilitates the comparison of standardised coefficient values for individual variables. The self-financing indicator demonstrates the most discriminating capacity.

Table 8: Standardized canonical discriminant function coefficients

Financial indicator	Value of standardized coefficients
Self-financing ratio	0.750
Financial leverage ratio	0.357
Insolvency ratio	-0.333
Current ratio	0.212
Return on equity	0.590
Credit period ratio	-0.203

Source: own elaboration based on output from IBM SPSS

Table 9 presents the values of the unstandardised coefficients for the canonical discriminant function.

Table 9: Canonical discriminant function coefficients

Financial indicator	Value of unstandardized coefficients
Self-financing ratio	1.184
Financial leverage ratio	0.034
Insolvency ratio	-0.021
Current ratio	0.099
Return on equity	0.976
Credit period ratio	-0.003
Constant	0.158

Source: own elaboration based on output from IBM SPSS

Utilising the values of unstandardised coefficients, the subsequent model was formulated:

$$\begin{aligned} \mathrm{y} = 0.158 + 1.184 \cdot \text{Self financing ratio} + 0.034 \\ \cdot \text{Financial leverage ratio} - 0.021 \cdot \text{Insolvency ratio} \\ + 0.099 \cdot \text{Current ratio} + 0.976 \cdot \text{Return on equity} \\ - 0.003 \cdot \text{Credit period ratio} \end{aligned} \tag{22}$$

Table 10 presents centroids for distinct groupings of businesses. The study only concentrated on contrasting the computed sign of the Z-score with the sign of the centroid. A positive Z-score indicates that the firm might be categorised as prosperous. If the Z-score is negative, the enterprise is deemed unprosperous.

The model's classification capability was evaluated using the identical dataset (sample of business entities) on which it was developed. Table 11 facilitates the comparison between actual and expected classifications, enabling the precise determination of the number of correctly

Table 10: Functions at group centroids

	Centroids
0 (prosperous business entity)	1.109
1 (non-prosperous business entity)	-1.109

Source: own elaboration based on output from IBM SPSS

categorised business enterprises. In the analysed data sample, 186 firms were accurately categorised out of a total of 204 enterprises. The model's total accuracy is 91.2% for accurately predicted situations. 96.1% of firms were accurately categorised as affluent, while 86.3% were categorised as unprosperous.

Table 11: Validation on the sample of enterprises

Classification results					
			Predicted group membership		
			prosperous	non-prosperous	Total
Original	Count	prosperous	98	4	102
		non-prosperous	14	88	102
	%	prosperous	96.1%	3.9%	100%
		non-prosperous	13.7%	86.3%	100%
91.2% of original grouped cases correctly classified.					

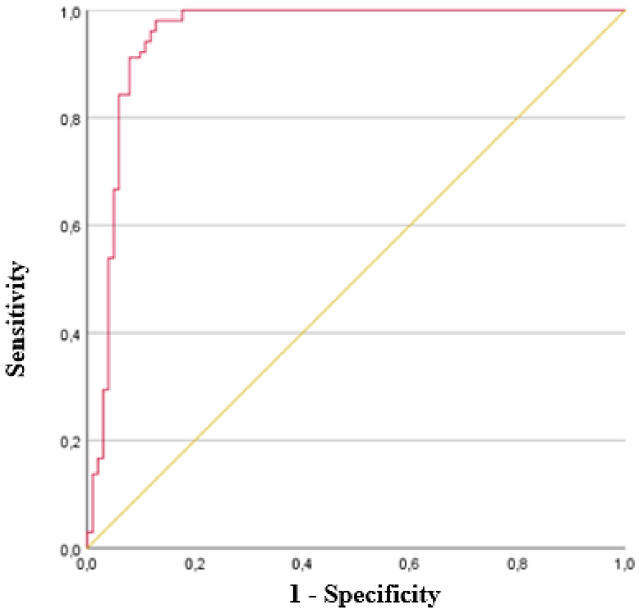
Source: own elaboration based on output from IBM SPSS

The primary instruments for evaluating model quality and comparing models are the classification table and the ROC curve, specifically the area under this curve (AUC). The AUC value assesses the model's prediction capability. If the AUC value is about 0.5, the model's predictive capability is negligible or feeble. If the value lies within the range of 0.7 to 0.8, the model's quality is considered high. If the interval is 0.8 to 0.9, the model quality is excellent. In this scenario, a score over 0.9 indicates outstanding model quality (Durica et al., 2023).

Figure 1 illustrates the classification ability of the prediction model for the post-COVID era, represented by the ROC curve derived from data pertaining to small and medium-sized enterprises within a NACE C sample. The area under the curve attains a value of 0.952. This rating reflects the model's excellent excellence.

Figure 1: ROC curve

ISSN 1337-0839 (print) / 2585-7258 (online)



Source: own elaboration based on output from IBM SPSS

4. Discussion

The prediction of corporate bankruptcy and economic distress is of interest to several stakeholders, including business entities, financial institutions, investors, regulatory agencies, auditors, and scholars. Diverse statistical and artificial intelligence techniques have been developed to yield more precise forecasts (Zhao et al., 2024a). Knowledge of impending bankruptcy is essential for financial institutions, managerial decision-makers, and governmental authorities. Given that bankruptcy prediction is a well-studied subject, several novel methodologies have been consistently introduced (Gnip et al., 2025). Increasing indebtedness can pose a challenging financial predicament for businesses, resulting in default and an incapacity to fulfil their impending liabilities (Gajdosikova et al., 2023).

Valaskova et al. (2023) create a model that predicts bankruptcy utilising financial data from 20,693 business entities across various sectors in the Visegrad group nations during the post-pandemic period (2020-2021) and find key predictors of bankruptcy. The authors employed multiple discriminant analysis to construct separate prediction models for each Visegrad Group nation, as well as a comprehensive model for the whole Visegrad Group. Conventional predictive methods, such as logistic regression and discriminant analysis, are limited by their incapacity to manage complicated and high-dimensional data. Recent advancements in machine learning, namely autonomous learning classifiers, provide a promising alternative (Sabek et al., 2024). Corporate bankruptcies frequently result in significant repercussions for all stakeholders, including financial investors forfeiting their capital and employees being laid off. Traditional bankruptcy prediction models primarily concentrate on forecasting the occurrence of bankruptcy, neglecting the socio-economic ramifications of their predictions. Consequently, Radovanovic and Haas (2023) concentrate on integrating these opinions into the machine-learning (ML) modelling process to consider for various expenses associated with bankruptcy. Predictions of business defaults are utilised in several sectors throughout the economy. Numerous recent studies endeavour to predict company insolvency employing diverse machine learning methodologies. Noh (2023) examine bankruptcy prediction models, including logistic regression, k-nearest neighbour, decision tree, and random forest, for the period from 2012 to

2021. Charalambous et al. (2023) establish a framework to concurrently calculate the latent parameters inherent in structural-parametric models for bankruptcy prediction. Horvathova et al. (2023) create a dynamic bankruptcy prediction model utilising a rarely applied approach, specifically graph theoretical modelling. A dynamic model incorporating the causal relationship among financial variables was developed for the period 2015-2021. Kanasz et al. (2023) introduced an innovative bankruptcy prediction method with a shallow autoencoder ensemble optimised by a genetic algorithm. To far, most research has concentrated on generating forecasts utilising artificial intelligence models that are supplied just with accounting data or a mixture of accounting data and additional categories of information. Zhao et al. (2024b) propose novel corporate governance mechanisms that use relational information within corporations by using the networks of boards of directors and the notion of node embeddings, which include mapping extensive director networks to lower-dimensional spaces. The impact of these additional factors on overall predictive performance they evaluated by using data from UK firms listed on the London Stock Exchange. Predicting bankruptcy is essential for evaluating financial risks and facilitating informed decision-making for investors and regulatory authorities. With the advancement of machine learning techniques, there has been significant interest in bankruptcy prediction because to its ability to manage complex data patterns and enhance predictive accuracy (Mate et al., 2023). Assessing the bankruptcy risk of small and medium-sized firms (SMEs) is essential for informed loan decision-making. Current research in finance and AI predominantly focusses on either intra-risk or contagion risk of business entities, neglecting their interconnections and combinatorial consequences. Wei et al. (2024) for the first time examine both categories of risk and their combined impact on bankruptcy prediction. Authors propose an enterprise intra-risk encoder grounded in statistically significant enterprise risk indicators for intra-risk learning. They offer an enterprise contagion risk encoder utilising an enterprise knowledge graph for contagion risk embedding.

5. Conclusions

The goal of this article was to assess the financial health of SMEs in Slovak manufacturing and to develop a predictive model that identifies financially distressed firms using key financial ratios. It examined the development of financial indicators related to activity, liquidity, profitability, and indebtedness over the period from 2018 to 2023. By applying statistical tools such as the Friedman test, the study confirmed that time had a statistically significant influence on the values of all selected financial indicators. Additionally, the research developed a predictive model through discriminant analysis using financial data from 2022 to forecast business prosperity in 2023. The model demonstrated high accuracy, correctly classifying 91.2% of firms, with a strong predictive quality indicated by an AUC value of 0.952.

Despite its strengths, the study encountered several limitations and barriers. One limitation was the scope of data, as the analysis included only those enterprises that operated continuously throughout the six-year period, excluding younger or more volatile firms whose financial trajectories might differ. Another constraint was the exclusive focus on the industrial sector (NACE C), which restricts the applicability of the findings to other sectors of the economy. Moreover, the classification model simplified firm prosperity into a binary outcome based solely on the equity-to-liabilities ratio, potentially overlooking more nuanced aspects of financial health. The model also did not account for broader macroeconomic variables such as inflation, interest rates, or international market influences, all of which may have a considerable impact on firm performance. The classification ability was tested based on training data; it did not use a test sample of enterprises. Additionally, given the dynamic economic environment

 ISSN 1337-0839 (print) / 2585-7258 (online)

following the COVID-19 pandemic, the long-term reliability of the model may be subject to change.

To address these limitations and deepen the understanding of SME financial stability, future research could expand the scope to use a test sample of enterprises from manufacturing and then include multiple economic sectors for cross-sectoral comparison. Incorporating external macroeconomic indicators and qualitative variables, such as innovation capacity or managerial effectiveness, could enhance model robustness. Further, applying advanced machine learning methods may allow for more complex and flexible prediction models. Lastly, examining regional disparities and conducting longitudinal studies on firm survival could provide more comprehensive insights into the financial resilience of SMEs in Slovakia.

Author contributions: All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: 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.

Conflicts of Interest: The authors declare no conflict of interest.

References

Act 513/1991 Coll—Slovak Commercial Code. Online. https://www.slov-lex.sk/ezbierky/pravne-predpisy/SK/ZZ/1991/513/

Bugaj, M., Durana, P., Blazek, R., & Horak, J. (2023). Industry 4.0: Marvels in profitability in the transport sector. *Mathematics*, *11*(17), 3647. https://doi.org/10.3390/math11173647

Charalambous, C., Martzoukos, S. H., & Taoushianis, Z. (2023). A neuro-structural framework for bankruptcy prediction. *Quantitative Finance, 23*(10), 1445-1464. https://doi.org/10.1080/14697688.2023.2230241

Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2023b). Business hybrid offerings by manufacturing SMEs: Impact of servitization on internationalization of manufacturing SMEs. *International Marketing Review*, *40*(4), 585-611. https://doi.org/10.1108/IMR-10-2021-0298

Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2021). Antecedents and consequence of social media marketing for strategic competitive advantage of small and medium enterprises: Mediating role of utilitarian and hedonic value. *Journal of Strategic Marketing*, *32*(8), 1106-1125. https://doi.org/10.1080/0965254X.2021.1954070

Chatterjee, S., Chaudhuri, R., Shah, M., & Maheshwari, P. (2022a). Big data driven innovation for sustaining SME supply chain operation in post COVID-19 scenario: Moderating role of SME technology leadership. *Computers & Industrial Engineering*, *168*, 108058. https://doi.org/10.1016/j.cie.2022.108058

Chatterjee, S., Chaudhuri, R., Vrontis, D., & Galati, A. (2023a). Influence of managerial practices, productivity, and change management process on organizational innovation capability of small and medium businesses. *European Business Review*, *35*(5), 839-859. https://doi.org/10.1108/EBR-02-2023-0049

Chatterjee, S., Chaudhuri, R., Vrontis, D., & Thrassou, A. (2022b). SME entrepreneurship and digitalization–the potentialities and moderating role of demographic factors. *Technological Forecasting and Social Change*, *179*, 121648. https://doi.org/10.1016/j.techfore.2022.121648

Chaudhuri, R., Chatterjee, S., Vrontis, D., & Chaudhuri, S. (2022). Innovation in SMEs, AI dynamism, and sustainability: The current situation and way forward. *Sustainability*, *14*(19), 12760. https://doi.org/10.3390/su141912760

Culkova, K., Tausova, M., Muchova, M., Domaracka, L. & Taus, P. (2018). Indebtedness in chosen industrial sectors with regard to economic development in the world. *Ekonomicky casopis, 66*(1), 28-42.

Das, S., Hassan, M., & Pachoni, P. (2023). Measuring financial health and performance of the oil and natural gas companies in India. *Indian Journal of Economics and Development*, *19*(4), 873-879. https://doi.org/10.35716/IJED-22475

Durana, P., Blazek, R. & Kovalova, E. (2024). Sherlock Holmes between homogeneity tests: Detection power based on profitability ratios in the V4 region. *Stats, 7*(4), 1333-1353. https://doi.org/10.3390/stats7040077

Durana, P., Kovalova, E., Blazek, R., & Bicanovska, K. (2025). Business efficiency: Insights from Visegrad four before, during, and after the COVID-19 pandemic. *Economies, 13*(2), 26. https://doi.org/10.3390/economies13020026

Durica, M., Frnda, J., & Svabova, L. (2023). Artificial neural network and decision tree-based modelling of non-prosperity of companies. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 18*(4), 1105-1131. https://doi.org/10.24136/eq.2023.035

Gajdosikova, D., Valaskova, K., Kliestik, T., & Kovacova, M. (2023). Research on corporate indebtedness determinants: A case study of Visegrad group countries. *Mathematics, 11*(2), 299. https://doi.org/10.3390/math11020299

Gnip, P., Kanasz, R., Zoricak, M., & Drotar, P. (2025). An experimental survey of imbalanced learning algorithms for bankruptcy prediction. *Artificial Intelligence Review, 58*(4), 104. https://doi.org/10.1007/s10462-025-11107-y

Horvathova, J., Mokrisova, M., & Baca, M. (2023). Bankruptcy prediction for sustainability of businesses: the application of graph theoretical modeling. *Mathematics, 11*(24), 4966. https://doi.org/10.3390/math11244966

Jencova, S., Miskufova, M., & Letkovsky, S. (2024). Is Logistic regression reliable in bankruptcy prediction?. *Journal of Management and Business: Research and Practice*, *16*(1),1-11. https://journalmb.eu/JMB/article/view/89

Jencova, S., Vasanicova, P., Stefko, R., & Lukacova, M. (2021). Financial analysis and competitiveness of public universities of Slovakia in the context of financial management. *Polish Journal of Management Studies*, *24*(2), 156-177. https://doi.org/10.17512/pjms.2021.24.2.10

Jihadi, M., Vilantika, E., Hashemi, S. M., Arifin, Z., Bachtiar, Y. & Sholichah, F. (2021). The effect of liquidity, leverage, and profitability on firm value: Empirical evidence from Indonesia. *Journal of Asian Finance, Economics and Business, 8*(3), 423-431. https://doi.org/10.13106/jafeb.2021.vol8.no3.0423

Kanasz, R., Gnip, P., Zoricak, M., & Drotar, P. (2023). Bankruptcy prediction using ensemble of autoencoders optimized by genetic algorithm. *PeerJ Computer Science, 9*, e1257. https://doi.org/10.7717/peerj-cs.1257

Kumar, V., Thrikawala, S. & Acharya, S. (2022). Financial inclusion and bank profitability: Evidence from developed market. *Global Finance Journal, 53*, 100609. https://doi.org/10.1016/j.gfj.2021.100609

Kliestik, T., Valaskova, K., Kliestikova, J., Kovacova, M., & Svabova, L., (2019). *Predikcia financneho zdravia podnikov tranzitivnych ekonomik.* University of Zilina in Zilina: EDIS.

Mate, D., Raza, H., & Ahmad, I. (2023). Comparative analysis of machine learning models for bankruptcy prediction in the context of Pakistani companies. *Risks, 11*(10), 176. https://doi.org/10.3390/risks11100176

Noh, S. H. (2023). Comparing the performance of corporate bankruptcy prediction models based on imbalanced financial data. *Sustainability, 15*(6), 4794. https://doi.org/10.3390/su15064794

Pavlicko, M., Durica, M., & Mazanec, J. (2021). Ensemble model of the financial distress prediction in Visegrad group countries. *Mathematics*, *9*(16), 1886. https://doi.org/10.3390/math9161886

Podhorska, I., & Siekelova, A. (2020). Enterprises financial performance in a globalized world. *SHS Web of* Conferences, *74*, 05018. https://doi.org/10.1051/shsconf/20207405018

Radovanovic, J., & Haas, C. (2023). The evaluation of bankruptcy prediction models based on socio-economic costs. *Expert systems with applications, 227*, 120275. https://doi.org/10.1016/j.eswa.2023.120275

Sabek, A., Horak, J., Musa, H., & Da Silva, A. F. (2024). Bankruptcy Prediction Using First-Order Autonomous Learning Multi-Model Classifier. *Statistika: Statistics & Economy Journal, 104*(4), 440–464. https://doi.org/10.54694/stat.2024.30

Stangova, N. & Vighova, A. (2021). Company Liquidity as a reflection of receivables and payables management. *Entrepreneurship and Sustainability Issues, 9*(2), 238-254. http://doi.org/10.9770/jesi.2021.9.2(16)

SK NACE (2025). *NACE C Manufacturing*. http://www.nace.sk/nace/c-sekcia-c-priemyselna-vyroba/

Valaskova, K., Gajdosikova, D., & Belas, J. (2023). Bankruptcy prediction in the post-pandemic period: A case study of Visegrad Group countries. *Oeconomia Copernicana, 14*(1), 253-293. https://doi.org/10.24136/oc.2023.007

Valaskova, K., Kliestik, T. & Gajdosikova, D. (2021). Distinctive determinants of financial indebtedness: Evidence from Slovak and Czech enterprises. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 16*(3), 639-659. https://doi.org/10.24136/eq.2021.023

Wei, S., Lv, J., Guo, Y., Yang, Q., Chen, X., Zhao, Y. & Kou, G. (2024). Combining intra-risk and contagion risk for enterprise bankruptcy prediction using graph neural networks. *Information Sciences, 659*, 120081. https://doi.org/10.1016/j.ins.2023.120081

Zhao, J., Ouenniche, J., & De Smedt, J. (2024a). Survey, classification and critical analysis of the literature on corporate bankruptcy and financial distress prediction. *Machine Learning with Applications, 15*, 100527. https://doi.org/10.1016/j.mlwa.2024.100527

Zhao, J., Ouenniche, J., & De Smedt, J. (2024b). A complex network analysis approach to bankruptcy prediction using company relational information-based drivers. *Knowledge-Based Systems, 300*, 112234. https://doi.org/10.1016/j.knosys.2024.112234