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Selection of over time stability ratios using machine learning techniques

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Abstract

According to the data provided by Coface platform, there are almost 3.8 million registered companies in the Visegrad Group (V4), with a significantly increased number of bankruptcies over the last years. Therefore, the main aim of this paper is to identify stable key indicators that determine the financial condition of these companies, which is of crucial importance for stakeholders and investors. To address this topic, we rely on the original dataset consisting of 145,638 company-years from the V4 countries, covering six main sectors during the period of 2018-2021. We calculate 78 financial and non-financial ratios, and we build a robust framework for the identification of the most important ones. Our framework relies on explainable machine learning techniques followed by cross-country and cross-sectional comparisons of the indicators. The results reveal that most of the non-financial indicators included in the analysis are important in assessing the financial condition of companies.

Keywords: *random forest, GINI index, Shapley values, financial distress, COVID-19*

1. Introduction

There is a very large number of enterprises that operate in the market, especially in the Visegrad Group (V4), which disappear from the market for various reasons, including financial ones. Financial standing analysis allows companies and their business partners to be assessed by evaluating both financial and non-financial indicators. The number of such indicators is also very large, affecting computational power, interpretability and evaluation. Consequently, reducing their number to the most important ones is of crucial importance. The selection of indicators should be limited to those that possess specific characteristics, such as predictive and discriminative capabilities, as well as stability over time. This last characteristic of indicators is gaining importance as repeated market crises demonstrate that only

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indicators that are characterized not only by predictive and discriminatory capabilities but, above all, by stability over time are relevant. This implies that these indicators have the same capabilities regardless of whether or not an economic crisis occurs.

The selection of indicators is typically made at the stage of building models for the prediction of corporate bankruptcy. The most recognizable models worldwide include [5], [3], and [44]. On the other hand, the models recognized in the V4 countries are the model of [35] (Poland), [40] (Czech Republic), [20] (Hungary), [10] (Slovakia), and [30] (V4). The structure of these models differs, among others, in the number of indicators analyzed and the number of final indicators selected for the model [62]. However, very little research has been done on the stability of the selected indicators. It often happens that the models do not demonstrate the high accuracy in predicting bankruptcy claimed by their authors. This issue is related to the selection of financial ratios to build such models.

The objective of this study is to examine the importance of ratios in the period before and during COVID-19 and the entire period as (2018-2021). Specifically, the aim is to determine whether and which indicators are important in the period under study. We use four concepts to define the importance of the features (ratios). Three of them are related to the random forest classifier: the mean decrease in Gini index, the mean decrease in accuracy, and the standard errors of the permutation-based importance measure. The fourth one relies on the Shapley values.

To achieve the goal of the article, we formulate the following research questions:

- RQ1. What percentage of the analyzed indicators can be considered as reliable in terms of their validity and stability over time?
- RQ2. Are there any repeatably (over time) reliable indicators in individual countries?
- RQ3. Are there any repeatably (over time) reliable indicators in individual sectors?
- RQ4. Are there any reliable non-financial indicators?

The paper is organized as follow. In section 2, we present basic related works. In section 3, we develop the methodology proposed in our study. In section 4, we demonstrate the results of our analysis. Then, in section 5, we compare the results from our methodology with those obtained from other relevant studies and we provide a discussion. Section 6 concludes the article.

2. Literature review

The global and regional literature in this area offers a vast number of indicators and a rich variety of selection methods [1, 62]. Indicator selection methods are typically used in developing bankruptcy prediction methods [12]. Statistical methods are subject to numerous limitations, therefore, the methods for indicator selection include a wide variety of techniques such as correlation analysis [2], t-test, stepwise, principal component analysis and factor analysis [32] and Wilska-Lambda index [50]. On the other hand, advanced methods used for bankruptcy prediction are not as limited as statistical methods and may employ other techniques, for example, grayscale image [24], gain ratio for selecting the most informative ratios [11], genetic algorithm and recursive feature elimination [32]. Notably, the selection methods used in the Visegrad Group countries (V4) also rely on a wide spectrum of techniques as presented in Table 1.

Table 1. Review of selection methods

Study	Sample	Period	Ratios	Selection methods	Important ratios
[6]	3,120 CZ	nd	5	GINI	5
[41]	1000 HU	2001-2012	17	t-test	7
[49]	66 PL	nd	28	Information Value, GINI, Vcramer	26
[7]	2,414 SK	2009-2013	5	ratios from Altman's model	5
[39]	241,380 CZ	2005-2013	30	univariate analysis	6
[53]	33 CZ	2013	12	maximum of accuracy	4
[64]	200 PL	2008-2013	64	normality test	5
[61]	20 PL	2007-2009	13	measure Ck	8
[70]	10,700 PL	2000-2012	64	DIS 0, random forrest	64
[17]	1,182 SK	2009-2014	102	stepwise	6
[26]	1,540 CZ	2011-2014	29	CART	5
[57]	1600 PL	2007–2016	5	normality test, correlation, t-test	1
[69]	nd	2009-2015	25	discriminant analysis	10
[67]	65,536 CZ	2008-2014	90	neural network	6
[4]	60 PL	2009-2013	42	correlation matrix, t-test	4
[21]	25 SK	nd	12	expert decision	5
[27]	1,355 CZ	2011-2014	28	stepwise	5
[29]	74,957 SK	2012-2015	11	stepwise	6
[30]	449,781 V4	2015-2016	37	stepwise	13
[31]	1828 HU	2015-2016	28	principal component analysis, Levenberg-Marquard algorithm	28
[37]	1,280 SK	2014-2017	58	stepwise	6
[66]	62,533 SK	2015	14	stepwise	9
[13]	29,000 PL	2016-2017	37	CART, CHAID	3
[16]	163,546 V4	2015-2016	37	Likelihood ratio test, R Square characteristics	17
[28]	4,420 CZ	2011-2015	35	stepwise	4
[42]	3370 HU	2001-2015	17	CHAID, stepwise	6
[43]	2996 HU	2007-2016	20	CHAID, stepwise	12
[19]	64,757 SK	2016-2018	14	stepwise	8
[22]	290 SK	2016	9	stepwise	5

Continue on next page

Study	Sample	Period	Ratios	Selection methods	Important ratios
[25]	44 PL	2010-2015	20	correlation matrix, Kolmogorov–Smirnov test, Shapiro–Wilk test, Wilks' Lambda test	12
[48]	3,679 PL	2018	22	genetic algorithms	19
[54]	343 SK	2016	9	stepwise	7
[56]	75,652 SK	2016-2018	11	stepwise	nd
[59]	10,700 PL	2000-2012	64	Kolmogorov–Smirnov test, t-test, correlation matrix, Wilks' Lambda test, stepwise	5
[23]	444 SK	2016	11	none	11
[36]	351 CZ	nd	14	stepwise	2
[51]	806 PL	2008-2010	21	t-test, chi-squared, correlation matrix	9
[46]	667,582 V4	2016-2018	27	stepwise	7
[47]	667,582 V4	2016-2018	27	minimal set of predictors	2
[15]	75,649 SK	2018-2019	25	missing values, multicollinearity	9
[45]	106,407 SK	2015-2019	46	feature importance	46
[60]	1500 V4	2009-2018	69	Kolmogorov–Smirnov test, t test, Wilks' Lambda test, stepwise	7
[65]	20,693 V4	2020-2021	18	stepwise	14

By analyzing Table 1, it is noticeable that the most commonly used method for ratios selection is the stepwise method. This is attributed to the fact that most models for corporate bankruptcy prediction were built on the basis of statistical methods in the V4. In addition to the stepwise method, correlation matrix and normality tests are also frequently used. On the other hand, there are selection methods such as GINI index, random forest, neural network, CART, CHAID, and feature importance that are less frequently used. Only one work concerns the COVID-19 period ([65]), but it does not take into account the time before and uses the most popular stepwise method for ratios selection. It should also be noted that there are few works taking into account large research samples ([30], [29], [66], [19], [56], [46], [65]), but once again they rely on the most-established ratios selection method, i.e., stepwise.

Contrary to the aforementioned methods, our research has three key advantages. First, we apply four feature importance concepts, using machine learning techniques, to select indicators, considering both the financial and non-financial sectors (a total of 78 indicators were analyzed). Second, we analyze the feature importance of the indicators in the period preceding and during the COVID-19 pandemic and over the entire period (2018-2021). We consider countries and sectors in the analysis to examine the stability of indicators over time. Third, we provide a large dataset of 145,638 firm-years covering the V4 (CZ, HU, PL, SK) from 2018 to 2021, that can be used to detect changes over time, country and sector. The companies belong to six sectors: manufacturing, construction, retail and wholesale trade, transportation and warehousing, and energy.

3. Methodology

In this article, we analyze the indicators for their stability over time. This multi-stage study covers the Visegrad Group countries. First, we obtained financial statements of enterprises operating in the Visegrad Group countries, broken down by country (CZ, HU, PL, SK) and as a whole (V4) as the sum of individual enterprises from each country. In addition to the country breakdown, the analysis also included a breakdown by sector: construction, manufacturing, wholesale and retail trade, transportation and warehousing, and energy (biomass electric power generation, wind electric power generation, fossil fuel electric power generation, hydroelectric power generation, and solar electric power generation). Financial statements were obtained from the EMIS (Emerging Markets Information Service) database (https://www.emis.com). Next, the study period was selected. Stability over time should encompass various periods, including periods with and without any crisis. Therefore, the period 2018-2021 was selected, which encompasses the period before COVID-19 (2018-2019) and during COVID-19 (2020-2021). Additionally, indicators for the entire period (2018-2021) were also examined. The total research sample is large and covers 145,638 company-years (see Table 3).

Then, 78 indicators were calculated for the research sample. These indicators belong to the following groups: financial liquidity, profitability, turnover, debt, growth, company size, and a second group that includes, among others, the form of business, the company's period of existence, the sector in which it operates, and the province in which it is registered (see Table 2). It is worth noting that the indicators belonging to the last group take values from a nominal scale adopted for them. For example, the indicator of the form of business can take values from a nominal scale of 1-4, where 1 means: joint-stock company, 2 means: limited liability company, 3 means: other limited liability company, and 4 means: limited joint-stock partnership. The indicator that divides companies into two classes is the equity. Companies with negative values of it are considered as (economically) bankrupt. Other researchers have also used negative equity, among others, to group companies [35], [34], [7], [39], [13], [22], [56], [55], [15], [14].

In the next step, we selected the variable selection methods utilized in this research and therefore in our analysis we use the notion of feature importance. Different concepts of feature importance are actively developed in the framework of interpretable machine learning. The reader is referred to the recently published book [38] for more details. We considered four concepts of the feature importance to select ratios. Three concepts are related to the random forest classifier: the mean decrease in Gini index, the mean decrease in accuracy, and the standard errors of the permutation-based importance measure. The concept based on the Shapley values was considered as well. These concepts will be briefly discussed below.

In the final step, we calculated the above-mentioned methods for the selected indicators over the analyzed period. We define the indicator as stable over time when the indicator was among the 10 most important indicators in the analyzed period (both before (2018-2019) and during the COVID-19 pandemic (2020-2021), as well as taking into account the entire 2018-2021 period) for at least one method.

Table 2. The ratios considered in the analysis.
Legend: NP – net profit; TA – total assets; TS – total sales; TL – total liabilities; CA – current assets; I – inventories; LL – long-term liabilities; log – logarithm; WC – working capital; CC – constant capital; SL – short-term liabilities; S – net sales; C – cash; R – receivables; OE – operating expenses; D – depreciation; RE – retained earnings; E – equity; GP – gross profit; FE – financial expenses; TC – total cost; FA – fixed assets; SC – share capital; OC – Operating cycle; CCC – cash conversion cycle

No.	Formula	No.	Formula	No.	Formula
X1	CA/CL	X27	EBIT/E	X53	(E-SC)/TA
X2	(CA-I)/CL	X28	EBIT/TC	X54	CC/TA
X3	(CA-I-R)/CL	X29	EBIT/FE	X55	CC/FA
X4	WC/TA	X30	NP/I	X56	LL/E
X5	WC/FA	X31	NP/FA	X57	CA/TL
X6	WC	X32	EBITDA/FA	X58	CL/TA
X7	WC/S	X33	RE/TA	X59	OE/CL
X8	WC/TL	X34	GP/CL	X60	OE/TL
X9	C/TA	X35	RE/CL	X61	log of TA
X10	I/WC	X36	S/TA	X62	log of S
X11	WC/E	X37	(I*365)/S	X63	log of (TA/GDP)
X12	EBIT/TL	X38	(R*365)/S	X64	S/Sn-1
X13	(GP+D)/TL	X39	(CL*365)/S	X65	TA/TA-1
X14	(NP+D)/TL	X40	S/I	X66	CA/CA-1
X15	(TL-C)/S	X41	S/R	X67	OP/OPn-1
X16	(TL-C)/EBITDA	X42	S/CL	X68	NP/NPn-1
X17	(NP+D)/CL	X43	S/FA	X69	I/In-1
X18	NP/TA	X44	OC (X37+X38)	X70	R/Rn-1
X19	GP/TA	X45	CCC (X37+X38-X39)	X71	CL/CLn-1
X20	EBIT/TA	X46	CA/S	X72	Industry by NAICS
X21	EBITDA/TA	X47	C/S	X73	Main sector
X22	NP/S	X48	(I+R)/E	X74	State
X23	GP/S	X49	TL/TA	X75	Number of Employees
X24	EBIT/S	X50	E/TL	X76	Legal Form
X25	EBITDA/S	X51	E/TA	X77	IncorporationDate ver. 1
X26	NP/E	X52	E/FA	X78	Incorporation Date ver. 2

For example, if X77 was selected as 1st in the pre-COVID-19 period, 5th in the COVID-19 period, and 10th for the entire 2018-2021 period, it was considered 1 for that method. If this occurred in every method, it is marked as 4 in the tables, indicating that the indicator was selected by all methods. The more methods used to identify a given indicator, the better. The results for countries as well as for sectors are presented in graphs (2, 3, 4, 5, 6, 7, 8, 9, 10, 11), and the symmetric results are presented in tables (4, 5, 6, 7, 8, 9, 10). A workflow diagram of the research is presented on the Figure 1.

Let us shortly recall all the used concepts of feature importance. Assume that the set of elements is divided in m classes. Let the elements be randomly classified according to the distribution of classes. The Gini index (Gini impurity) measures how often a randomly chosen element would be classified incorrectly. It can be calculated as follows:

Definition 1 ([9]). The Gini impurity is

$$\mathrm{Gini} = 1 - \sum_{c=1}^{m} p_c^2, \tag{1}$$

where p_c is the probability of object to be classified into class c.

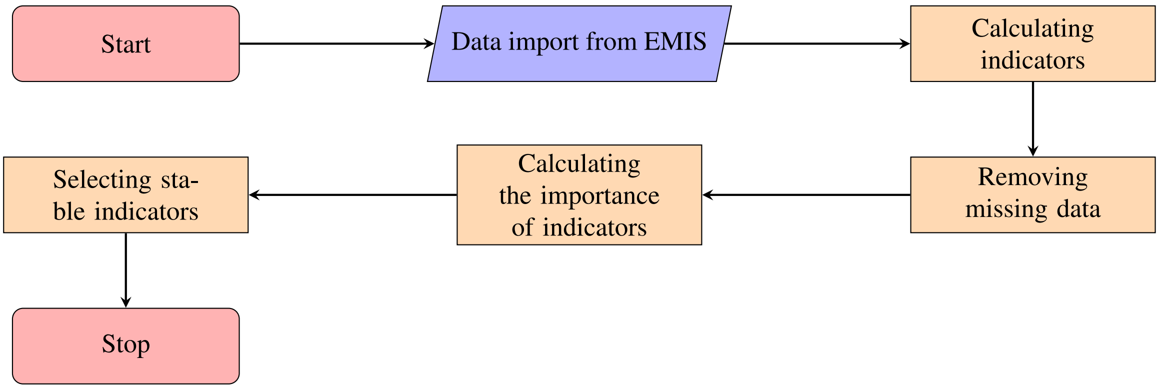

Figure 1. Workflow diagram of the research

The importance of a given feature with respect to the Gini index for a decision tree is equal to the decrease of the index summed over all splits for which this feature is used [9]. Random forests average the Gini index over all generated trees [8].

The mean decrease of accuracy is computed by permuting the original data. For each tree, the prediction error rate is recorded. Then, the same is done after permuting each feature. The difference between the two is the decrease of accuracy. Later, it is averaged over all the trees and normalized by the standard deviation of the differences [33].

The standard errors of the permutation-based importance measure are computed in the same way as the mean decrease of accuracy, but the standard error of regression is used instead of the prediction error rate [33].

The Shapley values were introduced in [52] in a framework of coalitional game theory as a measure of each player's contribution to the gain of coalition. Let a function $v(S)$, that measures the gain for every possible coalition S chosen from n players, be given.

Definition 2 ([52]). The Shapley value of the player i is

$$\mathrm{Shapley}(i) = \sum_{S \subset N \setminus \{i\}} \frac{|S|!(n-|S|-1)!}{n!} \big(v(S \cup \{i\}) - v(S)\big), \tag{2}$$

where N denotes the set of all players, and the sum extends over all subsets of N not containing i, including the empty set.

The authors of the article [68] suggested to interpret the Shapley values as a contribution of individual feature to data classification. In this interpretation the data features are the "players" and the gain function v represents the model used for the target variable prediction. The Shapley values are interpreted as the importance of the feature for prediction in the chosen model.

In our experiments we used the standard R implementation of the random forest [33]. For the Shapley values the fastshap R package [18] was used. As a user-specified prediction wrapper we used the random forest classifier. All the functions were used with the default parameterization. The code of the project and sample dataset with user's instruction are available on Gitlab[1].

The structure of the data after preprocessing (we removed all records with missing information) is presented in Table 3.

[1] https://gitlab.com/adenisiuk/companies

Table 3. Datasets statistics: b/a, where b is the number of bankrupt companies, a is the number of all records.

Country	2018	2019	2020	2021	all
CZ	$40/3778$	$28/3513$	$0/1763$	$0/725$	$68/9779$
HU	$289/15848$	$109/15114$	$15/15614$	$4/14730$	$417/61306$
PL	$652/11135$	$702/16190$	$297/12649$	$69/10776$	$1720/50750$
SK	$745/5695$	$728/5696$	$703/6317$	$671/6095$	$2847/23803$
sum:	$1726/36456$	$1567/40513$	$1015/36343$	$744/32326$	$5052/145638$

4. Results

We used four methods: RF, GINI, SD, and Shapley to assess the stability of the analyzed indicators over the period 2019-2021. The sample consists of four countries (CZ, HU, PL, SK) and the V4 as a whole, and six sectors (construction, manufacturing, wholesale and retail trade, transport and warehousing, and energy). In Figures 7, 8, 9, 10, and 11 the first rows from the left present the results for the construction and manufacturing sectors, while the second rows from the left present the wholesale and retail trade sectors, and the third rows from the left present the transport and warehousing and energy sectors. We focused on the time before and during COVID-19 (2018-2019), as well as the entire period (2018-2021). The figures summarize the results for both countries and individual sectors for the analyzed period. The treemaps show only those indicators that were able to distinguish companies both before and during the COVID-19 pandemic, as well as throughout the entire period. The larger the shape with the indicator number, the more frequently it appears in each method. The largest shapes reflect indicators appearing in all methods.

4.1. The most common indicators for all sectors for each V4 country

4.1.1. The most common indicators for all sectors for CZ

Analyzing the significance of the indicators for the Czech Republic presented in Figure 2, it can be concluded that only two indicators, X38 (number of days sales outstanding) and X41 (receivables turnover ratio), are significant for all four selected methods. The fact that two indicators are turnover indicators and refer to receivables means that timely collection of receivables is crucial for companies operating in the Czech Republic. For the following indicators, their significance is demonstrated only for two methods (X35, X65, X67, X69, X70, X72 GINI and Shapley, X5, X36, X37, X39, X40, X42 RF and SD), and for the remaining eight indicators only for one method (X17, X61 according to RF, X10, X53 according to GINI, X58, X63 according to SD, X6, X33 according to Shapley).

4.1.2. The most common indicators for all sectors for HU

The results for Hungary presented in Figure 3 show that there are only four indicators, two of which are the same as for the Czech Republic (X38, X41), and the other two are different: X35 and X62. The first different indicator, the ratio of retained earnings to current liabilities (X35), is important because it refers to the situation in which a company uses retained earnings to cover or finance current liabilities, such as liabilities to suppliers, employee salaries, or other short-term loans. The second, company size (X62), measures the size of the company as measured by revenue. It is worth noting that all four indicators were selected using only one method. Indicators X38 and X41 were selected using the SD method, while

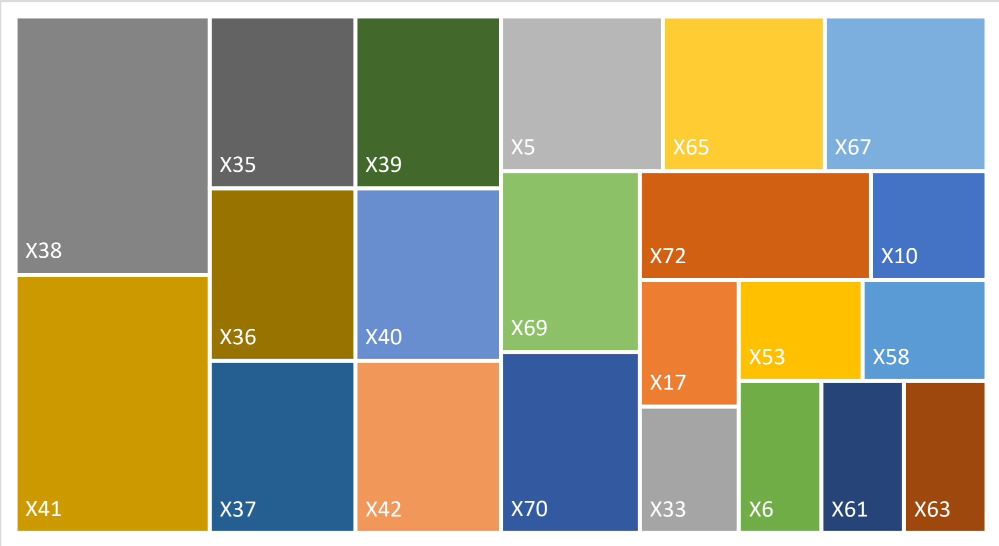

Figure 2. The most common indicators for all sectors for CZ.

indicators X35 and X63 were selected using the Sharpey method. Selecting indicators using only one method may imply that these indicators may not be as important as those selected using all methods.

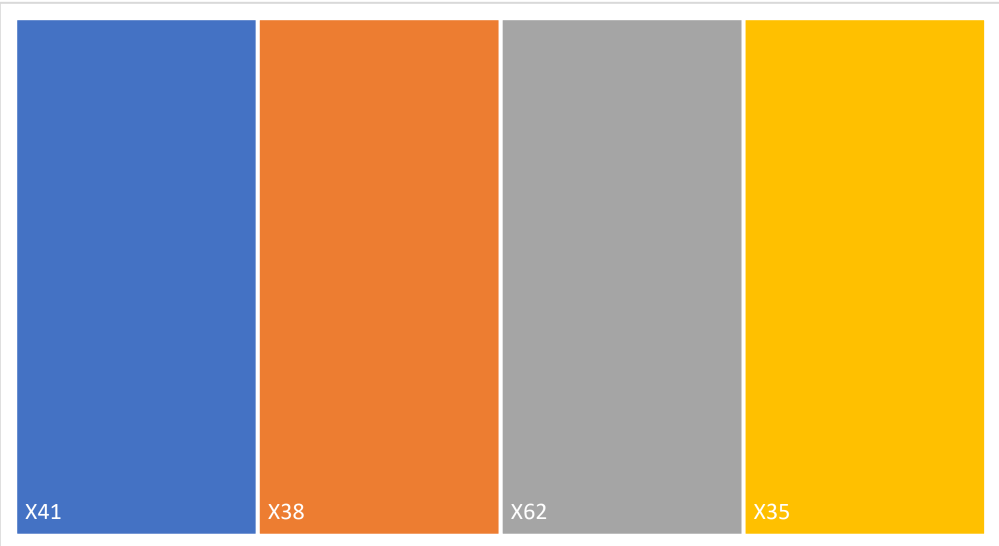

Figure 3. The most common indicators for all sectors for HU.

4.1.3. The most common indicators for all sectors for PL

In Poland, as in Hungary, no indicator was selected by all methods. However, compared to Hungary, five indicators were selected using two methods instead of one (see Figure 4). The fixed assets to working capital ratio (X5) was selected by RF and SD. It is a liquidity indicator, showing the degree to which working capital covers a company's fixed assets. Next, five indicators (X6, X76, X77, X78) were selected by the GINI and by the Sharley method. The first of these is also an indicator of liquidity, the value of working capital. The second concerns the legal form of the company. The last two concern the date of incorporation, implying that the company's age is important. The remaining ten indicators were selected as key indicators using only one method: X50, X53 (by RF), X61, X62, X63 (by GINI), X37, X39, X40, X42 (by SD), and X4 (by Sharpey).

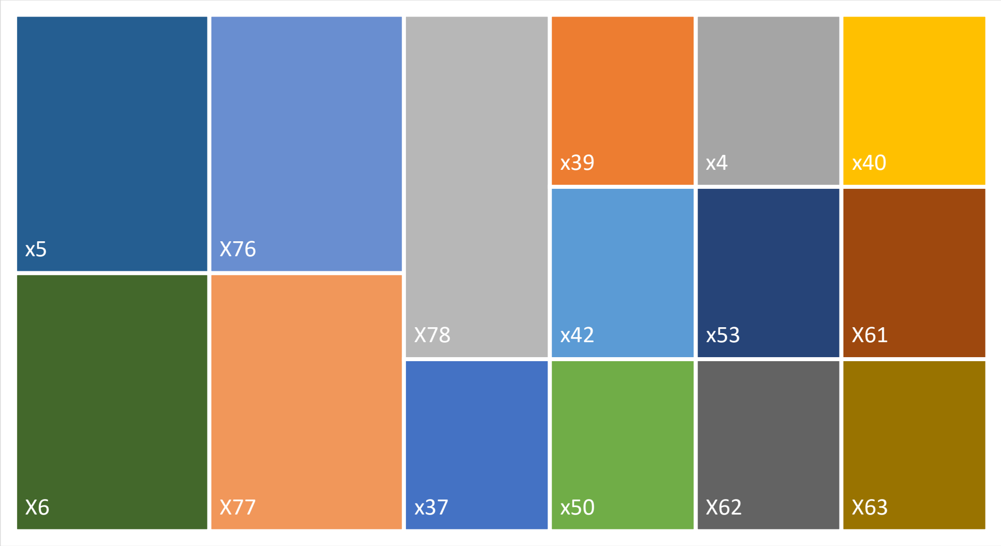

Figure 4. The most common indicators for all sectors for PL.

4.1.4. The most common indicators for all sectors for SK

Only eleven indicators are important for Slovakia, and for six of them, all methods indicate the same results (see Figure 5). The working capital ratio (X6) belongs to the group of liquidity indicators. The next three indicators are enterprise size indicators, measured by total assets (X61), revenue (X62), and total assets relative to GDP (X63). The fifth indicator is an indicator of the legal form of the enterprise (X76). The last indicator, X77, concerns the date of establishment of the company. Furthermore, X50 (according to the RF), X75, and X78 (according to Sharpey) proved crucial for one method.

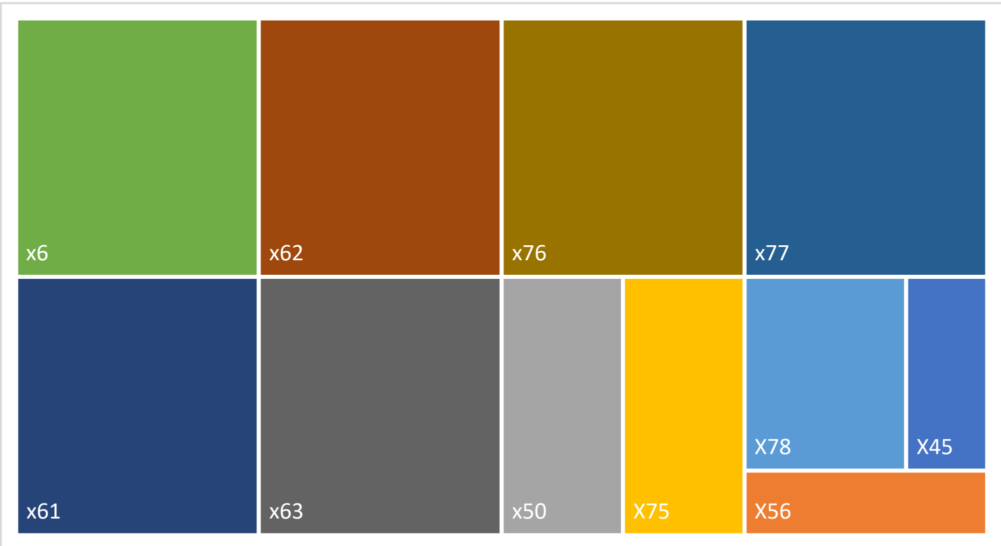

Figure 5. The most common indicators for all sectors for SK.

4.1.5. The most common indicators for all sectors for V4

Only one indicator, X74, was identified as significant by all methods in the analyzed periods (see Figure 6), which indicates the importance of the company's operating condition. Two indicators, X76 and X77, were significant for three methods. Furthermore, only half of the methods identified the next four indicators as significant: X35, X72, X75, and X78 (according to Gini and Sharpey). The remaining three indicators: X33, X45, and X53, were identified as key in assessing financial condition by only one method.

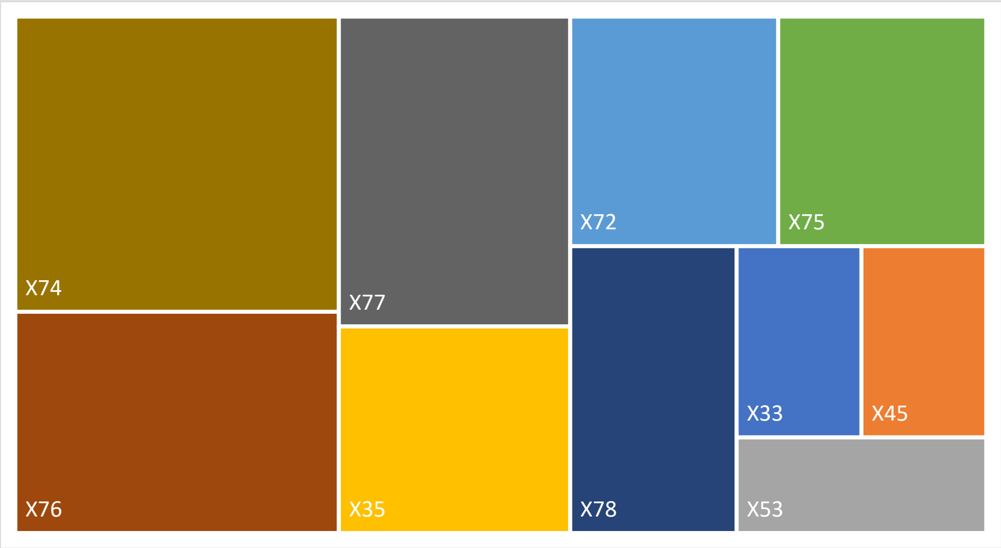

Figure 6. The most common indicators for all sectors for V4.

4.2. The most common indicators for each sector for each V4 country

4.2.1. The most common indicators for each sector for the entire V4

Analyzing Figure 7, which presents the aggregate results for all V4 countries divided into six sectors, reveals that some indicators are repeated regardless of sector. These include indicators X74 (the state in which the company is registered) and X76 (the legal form of the enterprise). Only for these two indicators the results of the methods are unambiguous, i.e., for each method in the periods 2018-2019, 2020-2021, and the entire 2019-2021 period, these indicators were selected as key in assessing the financial condition of V4 enterprises. It is worth noting that X77 (the date of company establishment) is also repeated for most sectors, excluding wholesale trade and energy generation.

However, analyzing the selected indicators for individual sectors, the results are exactly the same; in most cases, these two indicators were selected using four methods. In the wholesale sector, in addition to the aforementioned indicators, there is another indicator, X61 (the logarithm of total assets). In the wholesale sector, company size was also significant. For the transportation sector, in addition to the X74 and X76 indicators, the North American Industry Classification System (NAICS) industry index (X72) is important. The NAICS index shows the various industries within this sector.

4.2.2. The most common indicators for each sector for CZ

The indicators for the Czech Republic apply only to five sectors and do not apply to the energy sector, as there was no division into good and bad companies in this sector (see Figure 8). Furthermore, only for the manufacturing and transportation and warehousing sectors all methods selected one different indicator: X31 for the manufacturing sector and X35 for the transportation and warehousing sector. For the manufacturing sector, the profitability of fixed assets is important, while for the transportation and

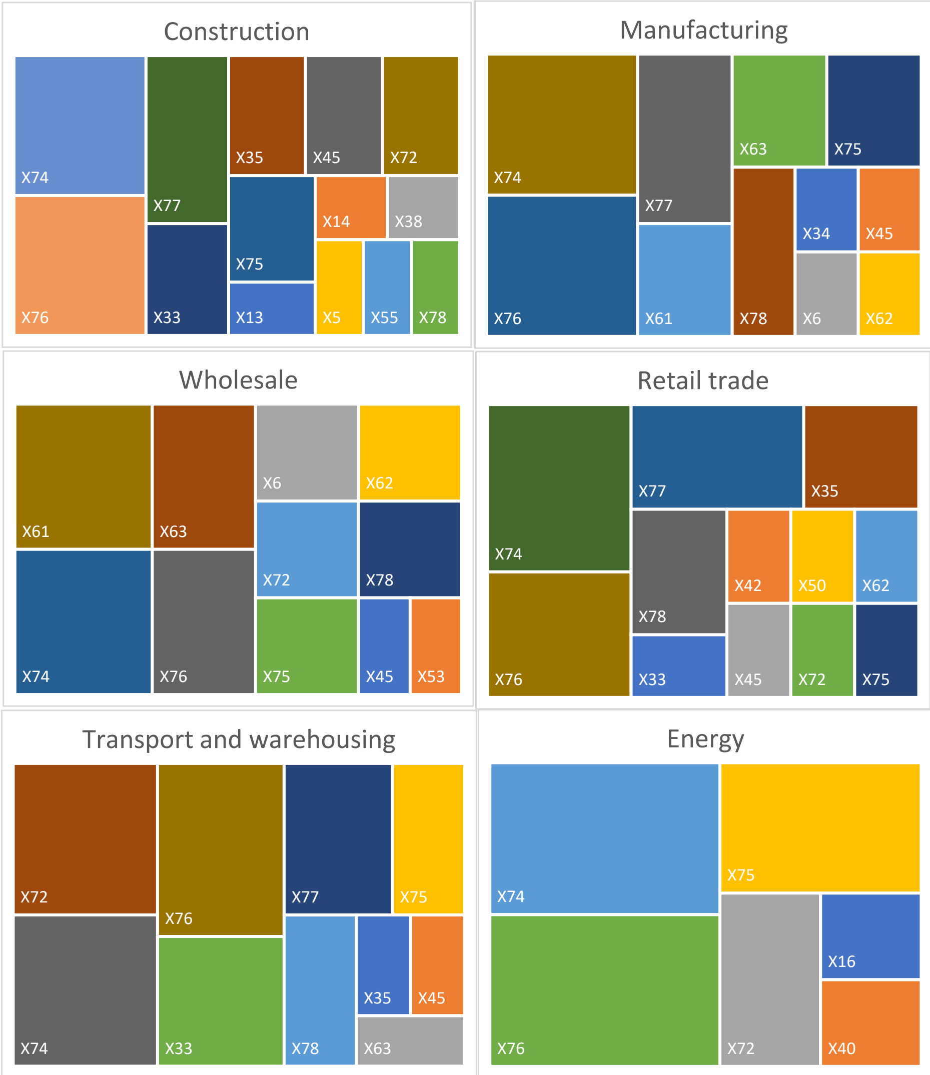

Figure 7. The most common indicators for each sector for the entire V4.

warehousing sector, the ratio of retained earnings to current liabilities is important. On the other hand, only three methods selected indicators for the construction, wholesale trade, and retail trade sectors. Two indicators are important for the construction sector: X11 (working capital to equity ratio) without the Gini index and X55 (fixed capital coverage ratio) without the RF index. Two indicators are also crucial for the retail trade sector: X36 (total asset turnover) and X44 (operating cycle) without the Gini index. Moreover, for wholesale trade, the key indicators are X3 (cash liquidity ratio), X17 (solvency ratio) without the Gini index and X41 (receivables turnover ratio) without the RF ratio.

4.2.3. The most common indicators for each sector for HU

When analyzing the indicators selected for the Hungarian economy, it should be noted that only one indicator was selected by all the methods for the energy sector (see Figure 9), namely X45 (cash conversion cycle). Considering the cost of transitioning to green energy for the sector, this is justified. Another important indicator for this sector is X48, selected using three methods. This indicator measures the share of inventories and receivables in equity. For the manufacturing sector, indicators were also selected using three methods: X4 (working capital), X18 (ROA measured by net profit), X19 (ROA measured by gross

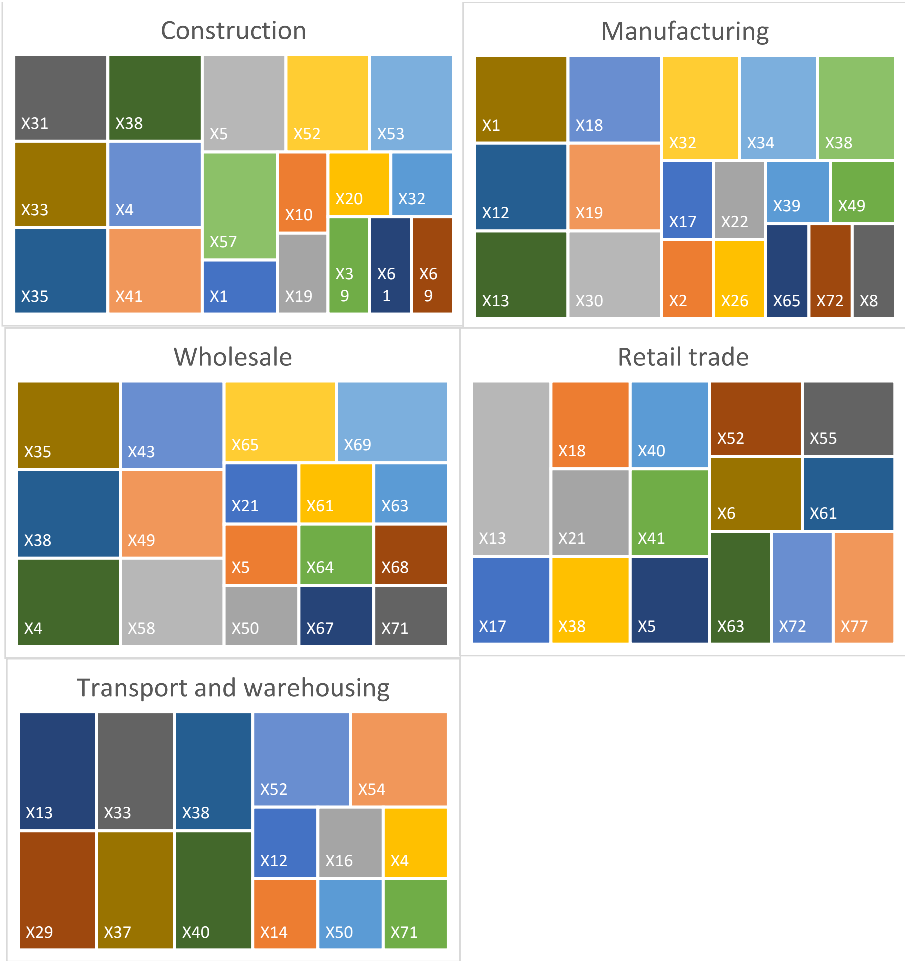

Figure 8. The most common indicators for each sector for CZ.

profit), and the previously mentioned X55. On the other hand, for the transportation and warehousing sector, six indicators were selected using only one method.

4.2.4. The most common indicators for each sector for PL

When analyzing the most frequently selected indicators for individual sectors of the Polish economy, it should be noted that only one indicator was selected for the transportation and warehousing sector, using all methods (see Figure 10). This was already mentioned before X78 (date of company incorporation, different classes than in X77). It is worth noting that X78 is also relevant for the following sectors: manufacturing, wholesale trade (selected using three methods), and retail trade (selected using two methods). For the manufacturing industry, the indicator selected using three methods is X5 (working capital to fixed assets ratio). Furthermore, for the energy sector, the indicator X70 (receivables growth rate) is significant, but selected using only two methods. Selecting indicators using only two methods may mean that for these two sectors they are less relevant and less stable over time.

4.2.5. The most common indicators for each sector for SK

Unlike the other analyzed countries, sectoral indicators for Slovakia were selected using all available methods (see Figure 11). These indicators often overlap between sectors. The core consists of four indicators: X61, X62, X63, and X76. These were the indicators mentioned earlier. In addition, X6

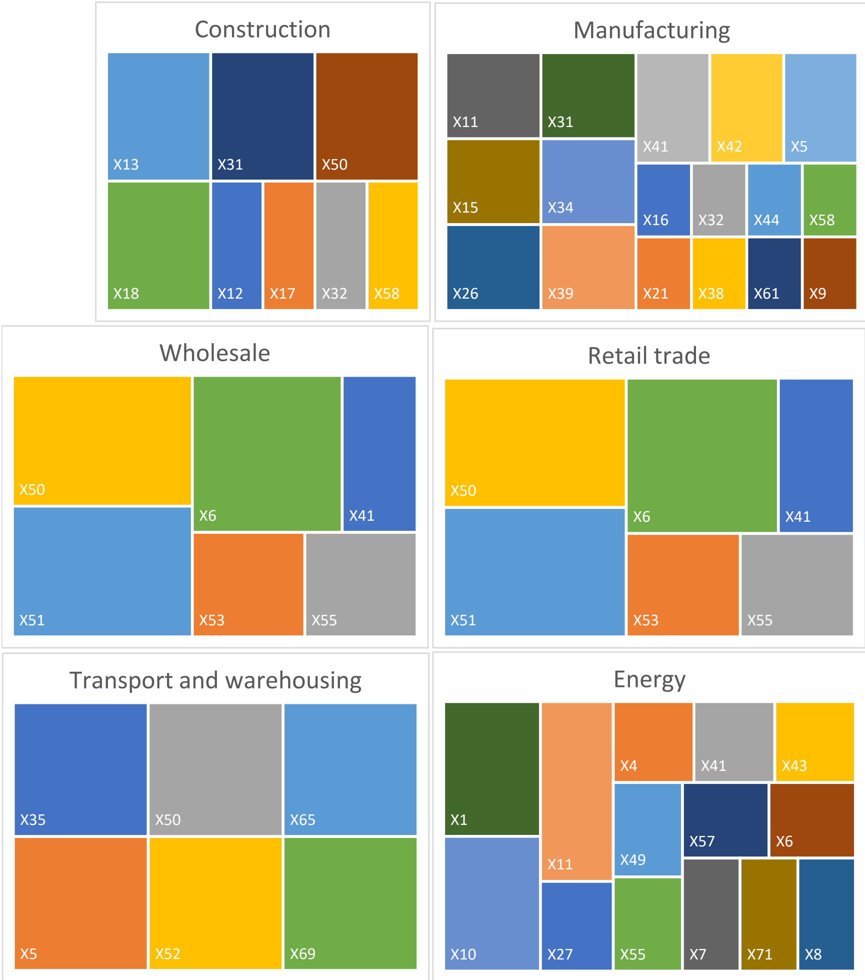

Figure 9. The most common indicators for each sector for HU.

and X77 were selected for the construction, manufacturing, wholesale, and retail sectors. X75 was selected for the manufacturing, wholesale, transportation and warehousing, and energy sectors. The final indicator, X72, was selected for the energy sector.

4.3. The summary of the results

Table 4 presents a summary of selected indicators for individual countries and the entire Visegrad Group (V4), without division into sectors. Tables 5, 6, 7, 8, 9, and 10 present selected indicators for individual sectors and countries. The figures 0 to 4 in the tables indicate the selection of a given indicator by the number of analyzed methods. For example, 4 means that the indicator was selected by all four analyzed methods, and 0 means that it was not selected by any of the methods.

Nineteen of the seventy-eight analyzed indicators are presented in Table 4. It should be noted that only X74 (the state in which the enterprise operates) was selected exclusively for the V4. The remaining indicators were selected for at least two countries. Analyzing the results for individual countries, it should be noted that for the Czech Republic, one indicator was selected using all methods: X38, the receivables turnover ratio, which was also selected for Hungary, but only by one method. Hungary is the only country with the smallest number of indicators, and they were selected by only one method. In addition to the above-mentioned X38, X35 and X62 were also selected. The selected indicators were also included in

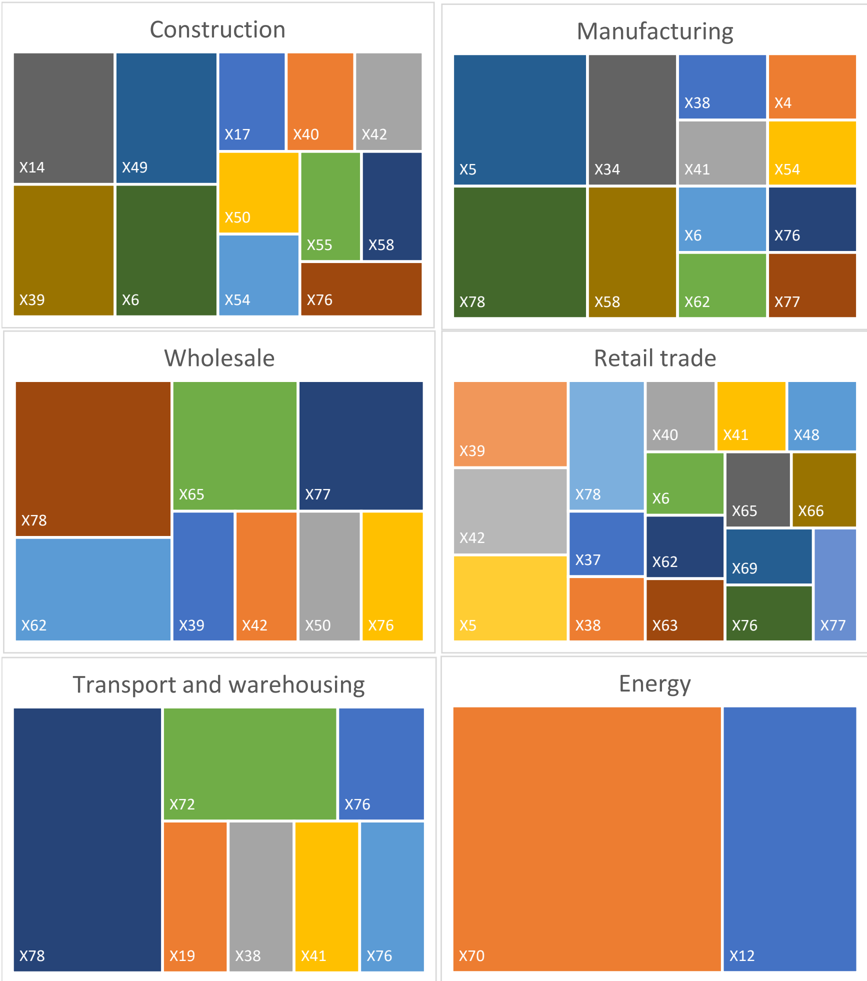

Figure 10. The most common indicators for each sector for PL.

the list of key indicators for the Czech Republic and V4, and X62 was also included for Poland and Slovakia. Furthermore, for both Poland and Hungary, no indicator was considered key by all methods. The indicators selected for Poland are X5 (working capital coverage ratio) and X6 (working capital value). For the Czech Republic, X5 is also significant, but indicated by two methods. For Slovakia, six indicators were selected using all methods: X6 (working capital), X61, X62, X63 (indicators measuring company size), X76 (legal form of the company), and X77 (date of company establishment). The first four are also relevant for the Czech Republic and Poland (without X62 for the Czech Republic, but for Hungary), but found to be stable by fewer methods. In contrast, for the V4, only one indicator was selected as key for all methods – X74. Furthermore, two indicators were identified as key for assessing financial condition using three methods: X76 and X77. These indicators are also key for Slovakia and Poland.

When analyzing indicators by sector, it should be noted that no single indicator was selected as key for each sector in each country. The first sector analyzed is the construction sector (see table 5). For this sector, only for Slovakia and the V4, indicators were selected using four methods. For the V4, these are three indicators (X72, X74, X76), while for Slovakia there are six (X6, X61, X62, X63, X76, X77). Only one indicator, X76, is repeated since it was selected using all methods and concerns the legal form of business activity. For the V4, important indicators include, in addition to legal status, company location

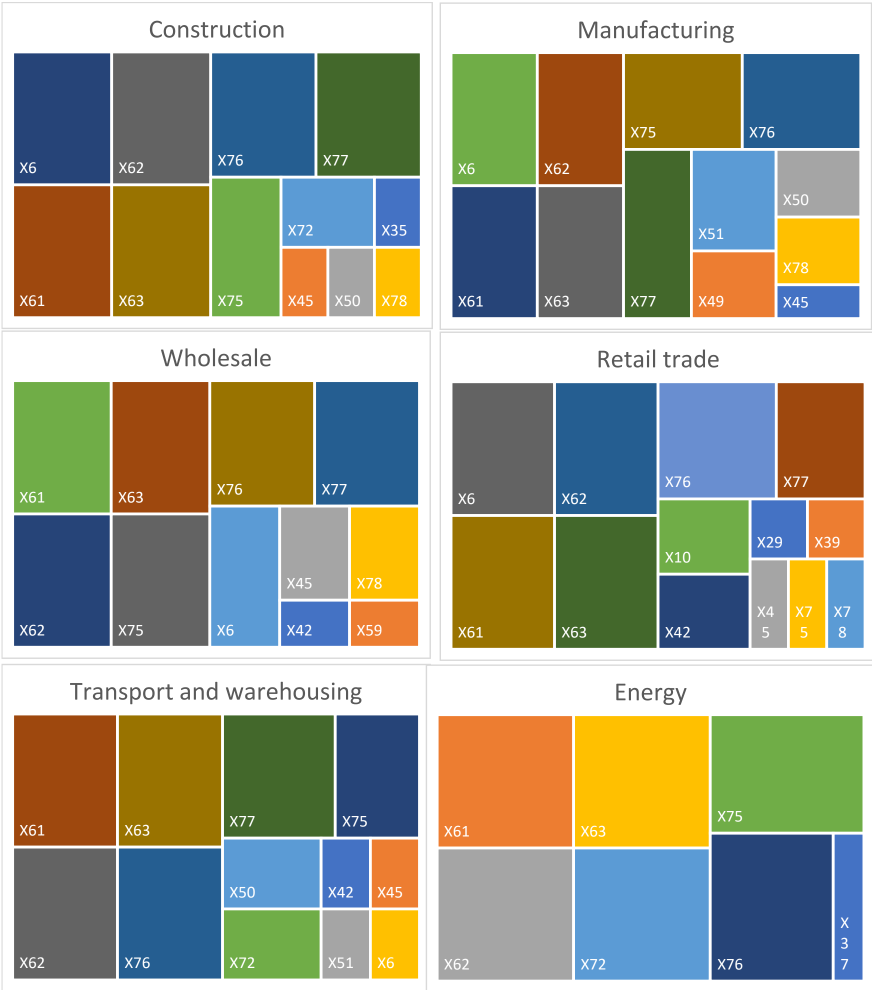

Figure 11. The most common indicators for each sector for SK.

and industry. For Slovakia, working capital, company size (measured in various ways), and company lifespan are important. On the other hand, for the Czech Republic, only two indicators were selected using three methods: X11 (working capital to equity) and X55 (fixed capital to fixed assets). Moreover, in the case of Hungary and Poland, the selection of indicators can only be observed using at most half of the methods.

The next sector analyzed is the manufacturing sector (see Table 6). For this sector, in addition to Slovakia and the V4, indicators were also selected for the Czech Republic using four methods. For the V4 and Slovakia, it is indicator X76, similarly to the construction sector. This is not the only indicator for the V4, but of the nine remaining indicators, only this one was selected as important by all methods. In the Czech Republic, there are also 10 indicators, and one was selected by four methods. This is X31 (net profit to fixed assets), which was also selected for Hungary, but only by half of the methods. Furthermore, for Hungary and Poland, there are 13 and 9 indicators, respectively. However, no indicator was selected as key by all methods for the manufacturing sector, as was the case for the construction sector. Three-quarters of the methods for Hungary selected X4, X18, X19, and X55 as key. For Poland, on the other hand, these methods identified X5, X6, and X78 as key. Moreover, in the case of Slovakia, in addition to the aforementioned X76, five more indicators were selected as important by all methods: X61, X62, X63, X75, and X77. These are almost the same indicators as in the construction sector, except that X6

Table 4. Summary of ratios for individual country

Ratios	CZ	HU	PL	SK	V4
X5	2	0	2	0	0
X6	1	0	2	4	0
X33	1	0	0	0	1
X35	2	1	0	0	2
X37	2	0	1	0	0
X38	4	1	0	0	0
X39	2	0	1	0	0
X40	2	0	1	0	0
X42	2	0	1	0	0
X50	0	0	1	2	0
X61	1	0	1	4	0
X62	0	1	1	4	0
X63	1	0	1	4	0
X72	2	0	0	0	2
X74	0	0	0	0	4
X75	0	0	0	2	2
X76	0	0	1	4	3
X77	0	0	1	4	3
X78	0	0	1	2	2

Table 5. Summary of ratios for individual country for construction sector.

Country	**X5**	**X6**	**X11**	**X13**	**X14**	**X31**	**X33**	**X35**	**X38**	**X39**
V4	1	0	0	1	1	0	2	2	1	0
CZ	2	0	3	0	0	2	2	2	2	1
HU	0	0	0	2	0	2	0	0	0	0
PL	0	2	0	1	2	0	0	0	0	2
SK	0	4	0	0	0	0	0	1	0	0

Country	**X45**	**X55**	**X61**	**X62**	**X63**	**X72**	**X74**	**X75**	**X76**	**X77**
V4	2	1	0	0	0	4	4	2	4	3
CZ	0	3	1	2	0	2	0	0	0	0
HU	0	0	0	0	0	0	0	0	0	0
PL	0	1	0	0	0	0	0	0	1	0
SK	1	0	4	4	4	2	0	3	4	4

has disappeared and in its place has appeared X75, which refers to the number of employees employed in the enterprise.

The third sector analyzed is the wholesale trade sector (see table 7). As with the previously analyzed sectors, only for Slovakia and the V4, indicators were selected using four methods. For Slovakia, the same set of six indicators was used as for the manufacturing sector. For the V4, it is slightly different but already well-known: X61 and X74. On the other hand, for the Czech Republic and Poland, one indicator was selected: X41 (receivables turnover ratio) for the Czech Republic and X78 (enterprise life expectancy indicator) for Poland. Furthermore, for Hungary, two of the four selected indicators, X6 and X50, were also selected for other countries. X6 was selected for Slovakia and the V4, and X50 for the Czech Republic and Poland. It is worth noting that the number of methods used to select these indicators did not exceed three.

The fourth sector analyzed is retail trade (see Table 8). Unlike the previously analyzed sectors, only for this sector a nearly identical set of variables was selected for Slovakia as for the construction sector.

Table 6. Summary of ratios for individual country for manufacturing sector.

Country	X4	X5	X6	X18	X19	X26	X31	X32	X34	X38
V4	0	0	1	0	1	0	0	0	1	0
CZ	0	0	0	2	2	1	4	2	2	2
HU	3	2	0	3	3	2	2	1	1	1
PL	1	3	3	0	0	0	0	0	0	1
SK	0	0	0	0	0	0	0	0	0	0
Country	**X39**	**X41**	**X55**	**X61**	**X62**	**X63**	**X75**	**X76**	**X77**	**X78**
V4	0	0	0	2	1	2	2	4	3	2
CZ	1	2	2	0	0	0	0	0	0	0
HU	2	2	3	1	0	0	0	0	0	0
PL	0	1	0	0	1	0	0	1	1	3
SK	0	0	0	4	4	4	4	4	4	2

Table 7. Summary of ratios for individual country for wholesale sector.

Country	X6	X41	X42	X45	X50	X53	X61	X62
V4	2	0	0	1	0	1	4	2
CZ	0	3	0	0	1	0	1	0
HU	2	1	0	0	2	1	0	0
PL	0	0	1	0	1	0	0	2
SK	3	0	1	2	0	0	4	4
Country	**X63**	**X65**	**X72**	**X74**	**X75**	**X76**	**X77**	**X78**
V4	3	0	2	4	2	3	0	2
CZ	1	2	2	0	0	0	0	0
HU	0	0	0	0	0	0	0	0
PL	0	2	0	0	0	1	2	3
SK	4	0	0	0	4	4	4	2

The difference lies in the X77 indicator, which was selected using only three methods. This indicator is also significant for the V4, which was also selected using three methods. Furthermore, the X76 indicator is also significant. It is worth noting that for the remaining countries, the X39 indicator (short-term liabilities cycle indicator) is equally significant, having been selected by half of the methods for the Czech Republic, Hungary, and Slovakia. The second such indicator is the X42 indicator (short-term liabilities turnover indicator), which was also selected by two methods for the Czech Republic, Poland, and Slovakia. It is very similar to the previous one; the difference is the swapping of the denominator and numerator and the multiplication of the number of days.

Table 8. Summary of ratios for individual country for retail sector.

Country	X5	X6	X13	X35	X38	X39	X40	X42	X45	X48
V4	0	0	0	2	0	0	0	1	1	0
CZ	1	1	2	0	1	2	1	2	0	2
HU	0	0	2	1	0	2	0	0	0	0
PL	2	1	0	0	1	2	1	2	0	1
SK	0	4	0	0	0	1	0	2	1	0
Country	**X50**	**X61**	**X62**	**X63**	**X69**	**X72**	**X75**	**X76**	**X77**	**X78**
V4	1	0	1	0	0	1	1	3	3	2
CZ	2	1	0	1	2	1	0	0	1	0
HU	2	0	0	0	0	0	0	0	0	0
PL	0	0	1	1	1	0	0	1	1	2
SK	0	4	4	4	0	0	1	4	3	1

Table 9. Summary of ratios for individual country for transport and warehousing sector.

Country	X6	X41	X42	X45	X50	X53	X61	X62
V4	3	1	0	0	1	0	0	0
CZ	2	4	2	3	0	1	2	3
HU	0	1	0	0	0	1	1	0
PL	0	0	1	1	0	0	0	0
SK	0	0	0	0	1	2	0	0
Country	**X63**	**X65**	**X72**	**X74**	**X75**	**X76**	**X77**	**X78**
V4	1	0	0	4	2	4	3	2
CZ	0	2	2	0	0	0	0	0
HU	0	1	1	0	0	0	0	0
PL	0	0	0	2	0	1	0	4
SK	4	0	0	2	3	4	4	0

The next sector analyzed is the transportation and warehousing sector (see Table 9). For this sector, with the exception of Hungary, the indicators for the other countries were selected using all methods. The core of these indicators is repeated across all sectors. For the V4, it is X76, for the Czech Republic X41, and for Poland X78. For Slovakia, the set of indicators is slightly smaller and consists of three: X63, X76, and X77. It is worth noting that for Hungary, the table contains five indicators. However, they were selected using only one method.

The final sector analyzed is the energy sector (see Table 10). It can be said that this table contains the smallest set of indicators of all the tables analyzed. It is also worth emphasizing that the Czech Republic has zeros because, as mentioned earlier, it was not possible to divide the sample of companies into healthy and unhealthy in this sector. Furthermore, Poland has one indicator, X70 (the short-term liabilities growth rate), which was selected using half of the methods. For the remaining countries, the indicators were selected using all four methods. The set for the V4 and Slovakia is standard, meaning it includes the same indicators as those presented earlier. For Hungary, for the first time, an indicator was selected using four methods: X45 (cash conversion cycle).

Table 10. Summary of ratios for individual country for energy sector.

Country	X16	X45	X61	X62	X63	X70	X72	X74	X75	X76
V4	1	0	0	0	0	0	0	4	0	4
CZ	0	0	0	0	0	0	0	0	0	0
HU	2	4	0	0	0	2	0	0	0	0
PL	0	0	0	0	0	2	0	0	0	0
SK	0	0	4	4	4	0	4	0	4	4

Based on the obtained results, the research questions posed can be answered. First, of the 78 indicators, 19 can be considered valid due to their validity and stability over time, representing 24% of the indicators analyzed. Second, of the 19 indicators presented, 18 are repeated across countries. It is worth noting that no indicator is repeated for all countries simultaneously; it is repeated for at most three countries. Third, as in the individual country analysis, there are valid indicators for individual sectors, but no indicator is repeated for all countries simultaneously for each sector; it is repeated for at most three countries. Fourth, most of the non-financial indicators included in the analysis appear together, indicating that they are valid based on the obtained results.

5. Discussion

The financial health of companies can be assessed using many indicators. However, useful are only those that have ability to distinguish healthy and unhealthy companies and are stable over time. The study focused on companies operating in post-communist countries such as the Czech Republic, Hungary, Poland, and Slovakia, as well as across the whole Visegrad Group.

The analysis includes 78 financial and non-financial indicators. From the indicators analyzed, 19 can be considered relevant for the analysis of individual countries. Six of them are non-financial indicators. For the Czech Republic, the most important indicator is X38 (receivables turnover ratio), which was also selected for Hungary. For Hungary, in addition to X38, there are X35 (retained profit to current liabilities) and X62 (size of company). It is worth noting that only these three indicators were selected using a single method. For Poland, these are X5 (working capital to fixed assets) and X6 (working capital). On the other hand, for Slovakia, in addition to X6, there are X61 (size of company measured by total assets), X62 (enterprise size measured by net sales), X63 (size of company measured by total assets/GDP), X76 (legal form), and X77 (incorporation date). The last two are non-financial indicators. In addition, non-financial indicators such as X74 (State), X76 and X77 are also important for the entire V4.

On the other hand, 20 of them can be considered relevant for sector analysis. The indicators listed above also seem crucial in this analysis. In addition, we can distinguish the following: X4 (working capital to total assets), X11 (working capital to equity), X18 (net profit to total assets), X19 (gross profit to total assets), X31 (net profit to fixed assets), X39 (payment term), X41 (receivables turnover ratio), X42 (current liabilities turnover ratio), X45 (cash conversion cycle), X55 (fixed capital to fixed assets ratio), X72 (industry by NAICS), X75 (number of employees), X78 (date of incorporation, version 2).

Table 11. Review of selection methods. Legend: E (GR) – equity growth ratios; OP – operating profit

Ratio	[30]	[16]	[46]	[47]	[60]	[65]	current research
TL/TA	x	x	x	x	x	x	
TL/R						x	
E/TL						x	
TL/E						x	
TL/CF						x	
NP+D/TL						x	
GP/S						x	
OP/S						x	
NP/S	x	x				x	
NP/A	x	x				x	x
NP/E	x	x	x			x	
C/CL	x				x	x	
CA-I/CL						x	
CA/CL	x	x	x		x	x	

Continue on next page

Ratio	[30]	[16]	[46]	[47]	[60]	[65]	current research
R*365/S						x	x
CL*365/S						x	x
S/TA		x	x	x		x	
I/S		x					
LL/TA		x					
WC/TA	x	x					
C/TA	x	x					
WC		x	x				x
OP/E	x						
OP/TA	x						
CA/TA	x						
CL/TA	x						
RE/TA					x		
EBIT/FE					x		
log of TA					x		x
(TL – C)/S					x		
(CA-I)/LL					x		
NP/I					x		
E/FA					x		
LL/E					x		
E (GR)					x		
X72							x
X74							x
X75							x
X76							x
X77							x
X78							x

Table 11 summarizes the indicators important in studies on V4 enterprises and adds those repeated from the current study, as well as important non-financial indicators. Only a few financial indicators are considered important compared to other studies. These include indicators representing liquidity, profitability, and company size, and two indicators of turnover. The company size indicator has also been used in other studies on the V4 as one of the few non-financial indicators ([41]; [70]; [26]; [42]). Another work that takes into account non-financial indicators is [45]. This work considers six non-financial indicators: sector, region, size, legal form, and age, as well as indicator significance characteristics. On the other hand, [51] found that a region with low risk and legal form is of significant importance. Therefore, it is important to also consider non-financial variables when assessing the financial health of enterprises.

When comparing the results obtained with other studies focused on V4 (Table 11), it should be noted that the current research differs in several respects. First, most studies focus on the use of statistical methods to build bankruptcy prediction models, which results in the primary use of the stepwise method as the primary method for selecting indicators. In our work, we use techniques from explainable machine learning to select the most important indicators. Second, these studies use a significantly smaller number of indicators analyzed. Typically, these are only financial indicators that do not take into account non-financial aspects, with the exception of the enterprise size indicator. In our work, in addition to the aforementioned enterprise size indicator, we also utilize a network of other indicators, most of which were deemed important in our research. Third, studies consider a different study period, usually not examining the stability of models over time, because they focus on two, or at most three, years, excluding the period before and during the crisis, with the exception of the study [60], which considers more years. In our paper, we consider the periods before and during the crisis.

It is also worth noting that no single indicator was identified as valid by all methods for every country or sector. This is partially attributed to the methods used, the period of analysis, and differences between countries and sectors. First, the definition of the indicator as stable over time, which is strict, has an impact on the results, as validation of existing models has shown a noticeable decrease in performance compared to the accuracy reported by the modelers ([63]; [58]). One reason for the decrease in model accuracy may be the use of indicators that are unstable over time, which will change the discriminatory power of the indicators used in a given model. Therefore, it is very important to study the stability of indicators over time. Second, based on the adopted definition of stability and the methods used, few indicators demonstrated stability over time, as recognized by all methods for both individual countries and sectors. This was partially due to the unbalanced sample, as there is significant inequality between healthy and unhealthy companies, both by country and by sector. This is due to data availability. Third, there are differences between countries and sectors that affect the result. This means that not every indicator can be considered to discriminate well healthy from unhealthy companies across all sectors and V4 countries. It is important to investigate which indicators can be used to build models for the entire V4. Research on this topic is ongoing, necessary and should be continued.

6. Conclusions

The main goal of this article was to select indicators based on their stability over time using machine learning techniques to identify financial distress of companies. The article contributes to the literature on forecasting corporate financial health in three ways. First, we utilize four feature importance concepts, using machine learning techniques, to select indicators, taking into account both financial and non-financial factors (a total of 78 indicators were analyzed). Most studies used only a stepwise selection approach and considered only financial indicators. However, most of the non-financial indicators included in the analysis are significant based on the obtained results. Second, we analyze the importance of indicator features in the periods before and during the COVID-19 pandemic, as well as throughout the entire period (2018-2021). We consider countries and sectors in the analysis to examine the stability of indicators over time. Only a small number of studies examine the stability of indicators over time. Third, we provide a large dataset covering nearly 150,000 company-years records, covering the V4 countries (CZ, HU, PL, SK) from 2018 to 2021. These companies belong to six sectors: manufacturing, construction, retail and wholesale trade, transportation and warehousing, and energy.

The results should be useful for managers, creditors, and investors, as key indicators were selected for each V4 country and sector. Furthermore, these key indicators were found to be stable over time, underscoring their importance and potential usefulness in predicting financial distress for companies, especially when it comes to using non-financial indicators.

A potential limitation of this study is that it only considers the period 2018–2021, which covers the situation before and during the COVID-19 crisis. A study that also includes other crises, such as the 2007 financial crisis, would allow comparisons of indicators between these periods. A second possible limitation is the limited focus on the selection of indicators as a basis for building models covering countries and sectors within the Visegrad Group. The third possible limitation is the uneven representation of data across countries and sectors, but this is due to data unavailability. Taking first two limitations in mind, future research could cover a much broader period that will also include the previous financial crises and machine learning methods will also be used to build models that predict financial distress.

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Credit authorship contribution statement

S.K.T: Conceptualization, Data curation, Methodology, Formal analysis, Funding acquisition, Investigation, Project administration, Resources, Supervision, Validation, Visualization, Writing – Original draft, Writing – Reviewing and Editing. A.D.: Conceptualization, Data curation, Methodology, Formal analysis, Investigation, Resources, Validation, Visualization, Writing – Original draft, Writing – Reviewing and Editing.

Data sources

Data sources related to this article can be found online at https://repod.icm.edu.pl/dataset.xhtml?persistentId=doi:10.18150/NMI1TU&faces-redirect=true

References

[1] Alaka, H. A., Oyedele, L. O., Owolabi, H. A., Kumar, V., Ajayi, S. O., Akinade, O. O., and Bilal, M. Systematic review of bankruptcy prediction models: Towards a framework for tool selection. *Expert Systems with Applications 94* (2018), 164–184.

[2] Alfaro, E., García, N., Gámez, M., and Elizondo, D. Bankruptcy forecasting: An empirical comparison of adaboost and neural networks. *Decision Support Systems 45*, 1 (2008), 110–122.

[3] Altman, E. I. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance 23*, 4 (1968), 589–609.

[4] Balina, R. Forecasting bankruptcy risk in the contexts of credit risk management – a case study on wholesale food industry in Poland. *International Journal of Economic Sciences 7*, 1 (2018), 1–15.

[5] Beaver, W. H. Financial ratios as predictors of failure. *Journal of Accounting Research 4* (1966), 71–111.

[6] Bemš, J., Starỳ, O., Macaš, M., Žegklitz, J., and Pošík, P. Innovative default prediction approach. *Expert Systems with Applications 42*, 17-18 (2015), 6277–6285.

[7] Bod'a, M., and Úradníček, V. The portability of Altman's Z-score model to predicting corporate financial distress of Slovak companies. *Technological and Economic Development of Economy 22*, 4 (2016), 532–553.

[8] Breiman, L. Random forests. *Machine learning 45*, 1 (2001), 5–32.

[9] Breiman, L., Friedman, J., Olshen, R. A., and Stone, C. J. *Classification and Regression Trees*. Taylor & Francis, 1984.

[10] Chrastinová, Z. *Methods for assessing economic viability and predicting the financial situation of agricultural enterprises*. Research Institute of Agricultural and Food Economics (Vỳskumnỳ ústav ekonomiky pol'nohospodárstva a potravinárstva), 1998 (in

Slovak).

[11] Cielen, A., Peeters, L., and Vanhoof, K. Bankruptcy prediction using a data envelopment analysis. *European Journal of Operational Research 154*, 2 (2004), 526–532.

[12] Dasilas, A., and Rigani, A. Machine learning techniques in bankruptcy prediction: A systematic literature review. *Expert Systems with Applications 255* (2024), 124761.

[13] Durica, M., Frnda, J., and Svabova, L. Decision tree based model of business failure prediction for Polish companies. *Oeconomia Copernicana 10*, 3 (2019), 453–469.

[14] Durica, M., Frnda, J., and Svabova, L. Financial distress prediction in Slovakia: An application of the cart algorithm. *Journal of International Studies 14*, 1 (2021), 201–215.

[15] Durica, M., Frnda, J., and Svabova, L. Artificial neural network and decision tree-based modelling of non-prosperity of companies. *Equilibrium. Quarterly Journal of Economics and Economic Policy 18*, 4 (2023), 1105–1131.

[16] Durica, M., Valaskova, K., and Janoskova, K. Logit business failure prediction in V4 countries. *Engineering Management in Production and Services 11*, 4 (2019), 54–64.

[17] Gavurova, B., Packova, M., Misankova, M., and Smrcka, L. Predictive potential and risks of selected bankruptcy prediction models in the Slovak business environment. *Journal of Business Economics and Management 18*, 6 (2017), 1156–1173.

[18] Greenwell, B. (2024) *fastshap: Fast Approximate Shapley Values*. R package version 0.1.1 (accessed on 5 August 2025).

[19] Gregova, E., Valaskova, K., Adamko, P., Tumpach, M., and Jaros, J. Predicting financial distress of Slovak enterprises: Comparison of selected traditional and learning algorithms methods. *Sustainability 12*, 10 (2020), 3954.

[20] Hajdu, O., and Virág, M. A Hungarian model for predicting financial bankruptcy. *Társadalom és gazdaság Közép- és Kelet-Európában/Society and Economy in Central and Eastern Europe 23*, 1/2 (2001), 28–46.

[21] Horváthová, J., and Mokrišová, M. Risk of bankruptcy, its determinants and models. *Risks 6*, 4 (2018), 117.

[22] Horváthová, J., and Mokrišová, M. Comparison of the results of a data envelopment analysis model and logit model in assessing business financial health. *Information 11*, 3 (2020), 160.

[23] Horváthová, J., Mokrišová, M., and Petruška, I. Selected methods of predicting financial health of companies: Neural networks versus discriminant analysis. *Information 12*, 12 (2021), 505.

[24] Hosaka, T. Bankruptcy prediction using imaged financial ratios and convolutional neural networks. *Expert Systems with Applications 117* (2019), 287–299.

[25] Jaki, A., and Ćwięk, W. Bankruptcy prediction models based on value measures. *Journal of Risk and Financial Management 14*, 1 (2020), 26.

[26] Karas, M., and Režňáková, M. Predicting the bankruptcy of construction companies: A CART-based model. *Inzinerine Ekonomika-Engineering Economics 28*, 2 (2017), 145–154.

[27] Karas, M., and Režňáková, M. Building a bankruptcy prediction model: Could information about past development increase model accuracy? *Polish Journal of Management Studies 17*, 1 (2018), 116–130.

[28] Karas, M., and Srbová, P. Predicting bankruptcy in construction business: Traditional model validation and formulation of a new model. *Journal of International studies 12*, 1 (2019), 283–296.

[29] Kliestik, T., Misankova, M., Valaskova, K., and Svabova, L. Bankruptcy prevention: New effort to reflect on legal and social changes. *Science and Engineering Ethics 24*, 2 (2018), 791–803.

[30] Kliestik, T., Vrbka, J., and Rowland, Z. Bankruptcy prediction in Visegrad group countries using multiple discriminant analysis. *Equilibrium. Quarterly Journal of Economics and Economic Policy 13*, 3 (2018), 569–593.

[31] Kristóf, T. The Application of case-based reasoning to predicting bankruptcy among domestic microenterprises. *Statisztikai Szemle 96*, 11-12 (2018), 1109–1128 (in Hungarian).

[32] Liang, D., Lu, C.-C., Tsai, C.-F., and Shih, G.-A. Financial ratios and corporate governance indicators in bankruptcy prediction: A comprehensive study. *European Journal of Operational Research 252*, 2 (2016), 561–572.

[33] Liaw, A., and Wiener, M. Classification and regression by randomForest. *R News 2*, 3 (2002), 18–22.

[34] Machek, O., Smrčka, L., and Strouhal, J. How to predict potential default of cultural organizations. In *Proceedings of the 7th International Scientific Conference Finance and Performance of Firms in Science, Education and Practice, Zlín, Czech Republic, April 23–24, 2015* (Zlín, 2015), E. Astuszková, Z. Crhová, J. Vychtilová, B. Vytrhlíková and A. Knápková, Eds., Univerzita Tomáše Bati ve Zlíně, pp. 893–902.

[35] Mączyńska, E., and Zawadzki, M. Discriminant models for predicting corporate bankruptcy. *Ekonomista*, 2 (2006), 205–235 (in Polish).

[36] Mazanec, J., and Bartosova, V. Prediction model as sustainability tool for assessing financial status of non-profit organizations in the Slovak republic. *Sustainability 13*, 17 (2021), 9721.

[37] Mihalovič, M. Applicability of scoring models in firms' default prediction. The case of Slovakia. *Politická ekonomie 66*, 6 (2018), 689–708.

[38] Molnar, C. *Interpretable Machine Learning*, 3 ed. Christoph Molnar (Leanpub), 2025.

[39] Němec, D., and Pavl'ik, M. Predicting insolvency risk of the Czech companies. In *Proceedings of the International Scientific Conference Quantitative Methods in Economics: Multiple Criteria Decision Making XVIII, 25th May - 27th May 2016 Vrátna, Slovakia*, M. Reiff, P. Gežík and M. Lukáik, Eds., Letra Interactive, s. r. o. (2016), pp. 258–263.

[40] Neumaier, I., and Neumaierova, I. Analysis of the value formation – application of financial analysis INFA. In *Sektorovéa odvětvové analýzy* (2001). Aspekt 8/V. Investiční strojírenství, vol. 6, pp. 23–39 (in Czech).

[41] Nyitrai, T. Predicting the bankruptcy of domestic firms based on data from financial statements one, two, or three years prior to the bankruptcy event. *Vezetéstudomány-Budapest Management Review 46*, 5 (2015), 55–65 (in Hungarian).

[42] NYITRAI, T. Dynamization of bankruptcy models via indicator variables. *Benchmarking: An International Journal 26*, 1 (2019), 317–332.

[43] NYITRAI, T., AND VIRÁG, M. The effects of handling outliers on the performance of bankruptcy prediction models. *Socio-Economic Planning Sciences 67* (2019), 34–42.

[44] OHLSON, J. A. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research 18*, 1 (1980), 109–131.

[45] PAPÍK, M., AND PAPÍKOVÁ, L. Impacts of crisis on SME bankruptcy prediction models' performance. *Expert Systems with Applications 214* (2023), 119072.

[46] PAVLICKO, M., DURICA, M., AND MAZANEC, J. Ensemble model of the financial distress prediction in visegrad group countries. *Mathematics 9*, 16 (2021), 1886.

[47] PAVLICKO, M., AND MAZANEC, J. Minimalistic logit model as an effective tool for predicting the risk of financial distress in the Visegrad Group. *Mathematics 10*, 8 (2022), 1302.

[48] PISULA, T. An ensemble classifier-based scoring model for predicting bankruptcy of Polish companies in the Podkarpackie Voivodeship. *Journal of Risk and Financial Management 13*, 2 (2020), 37.

[49] PISULA, T., MENTEL, G., AND BROŻYNA, J. Non-statistical methods of analysing of bankruptcy risk. *Folia Oeconomica Stetinensia 15*, 1 (2015), 7–21.

[50] POMPE, P. P. M., AND BILDERBEEK, J. The prediction of bankruptcy of small- and medium-sized industrial firms. *Journal of Business Venturing 20*, 6 (2005), 847–868.

[51] PTAK-CHMIELEWSKA, A. Bankruptcy prediction of small- and medium-sized enterprises in Poland based on the LDA and SVM methods. *Statistics in Transition. New Series 22*, 1 (2021), 179–195.

[52] SHAPLEY, L. S. A value for n-person games. In *Contributions to the Theory of Games II*, H. W. Kuhn and A. W. Tucker, Eds., Princeton University Press, Princeton, 1953, pp. 307–317.

[53] SLAVÍČEK, O., AND KUBĚNKA, M. Bankruptcy prediction models based on the logistic regression for companies in the Czech Republic. In *Managing and Modelling of Financial Risks: 8th International Scientific Conference* (2016), Vysoká škola báňská-Technická univerzita Ostrava, 924–931.

[54] ŠTEFKO, R., HORVÁTHOVÁ, J., AND MOKRIČOVÁ, M. Bankruptcy prediction with the use of data envelopment analysis: An empirical study of Slovak businesses. *Journal of Risk and Financial Management 13*, 9 (2020), 212.

[55] SVABOVA, L., DURICA, M., AND VALASKOVA, K. Failure prediction models for Slovak small companies. *European Journal of International Management 18*, 4 (2022), 617–637.

[56] SVABOVA, L., MICHALKOVA, L., DURICA, M., AND NICA, E. Business failure prediction for Slovak small and medium-sized companies. *Sustainability 12*, 11 (2020), 4572.

[57] TOMCZAK, S. K. The stability of the financial indicators over time. In *Information Systems Architecture and Technology: Proceedings of 38th International Conference on Information Systems Architecture and Technology – ISAT 2017, Part III* (Cham, 2018), Z. Wilimowska, L. Borzemski and J. Świątek, Eds., vol. 657 of *Advances in Intelligent systems and Computing*, Springer, pp. 98–107.

[58] TOMCZAK, S. K. Verification of the effectiveness of re-estimated discriminant models on the example of the food manufacturing sector. *Zarządzanie i Finanse 16*, 4.1 (2018), 193–205.

[59] TOMCZAK, S. K. Multi-class models for assessing the financial condition of manufacturing enterprises. *Contemporary Economics 14*, 2 (2020), 219–235.

[60] TOMCZAK, S. K. General bankruptcy prediction models for the Visegrád Group.The stability over time. *Operations Research and Decisions 33*, 4 (2023), 171–187.

[61] TOMCZAK, S. K., GÓRSKI, A., AND WILIMOWSKA, Z. The selection of variables in the models for financial condition evaluation. In *Information Systems Architecture and Technology: Proceedings of 36th International Conference on Information Systems Architecture and Technology–ISAT 2015–Part IV* (Cham, 2015), Z. Wilimowska, L. Borzemski, A. Grzech and J. Świątek (2016), Springer, pp. 39–49.

[62] TOMCZAK, S. K., KARAS, M., KRISTOF, T., DURICOVA, L., AND DURICA, M. Identification of key indicators, model development, and validation methods for bankruptcy prediction: A systematic review for the Visegrad Group. *Forum Scientiae Oeconomia 13*, 3 (2025), 156–196.

[63] TOMCZAK, S. K., AND RADOSIŃSKI, E. The effectiveness of discriminant models based on the example of the manufacturing sector. *Operations Research and Decisions 27*, 3 (2017), 81–97.

[64] TOMCZAK, S. K., AND WILIMOWSKA, Z. Testing the probability distribution of financial ratios. In *Information Systems Architecture and Technology: Proceedings of 36th International Conference on Information Systems Architecture and Technology–ISAT 2015–Part IV* (Cham, 2015), Z. Wilimowska, L. Borzemski, A. Grzech and J. Świątek (2016), Springer, pp. 75–84.

[65] VALASKOVA, K., GAJDOSIKOVA, D., AND BELAS, J. Bankruptcy prediction in the postpandemic period: A case study of Visegrad Group countries. *Oeconomia Copernicana 14*, 1 (2023), 253–293.

[66] VALASKOVA, K., KLIESTIK, T., AND KOVACOVA, M. Management of financial risks in Slovak enterprises using regression analysis. *Oeconomia Copernicana 9*, 1 (2018), 105–121.

[67] VOCHOZKA, M. Formation of complex company evaluation method through neural networks based on the example of construction companies collection. In *Innovation Management, Entrepreneurship and Sustainability (IMES 2018)*. Vysoká škola ekonomická v Praze, 2017, pp. 1119–1128.

[68] ŠTRUMBELJ, E., AND KONONENKO, I. Explaining prediction models and individual predictions with feature contributions. *Knowledge and Information Systems 41*, 3 (2014), 647–665.

[69] WÓJCICKA, A. Neural networks vs discriminant analysis in the assessment of default. *Annales Universitatis Mariae Curie-*

Skłodowska, Sectio H Oeconomia 51, 5 (2017), 339–349.

[70] Zięba, M., Tomczak, S. K., and Tomczak, J. M. Ensemble boosted trees with synthetic features generation in application to bankruptcy prediction. *Expert Systems with Applications 58* (2016), 93–101.