Identification of Key Indicators, Model Development, and Validation Methods for Bankruptcy Prediction: A Systematic Review for the Visegrad Group

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Abstract

Companies persist in encountering difficulties in navigating market conditions. To remain viable in the market, one must adapt rapidly to avoid obsolescence. These characteristics demonstrate increased diversity in the context of emerging markets, such as the Visegrad Group countries (V4). A multitude of financial distress models have been developed within the V4 to date. However, specialists from particular countries have yet to be convened for a comprehensive analysis of these models. The prior assessments overlook several publications. The objective of the article is to provide a novel comprehensive analysis of bankruptcy prediction models developed for the V4 countries and for the whole V4 region. It analyses the scientific publications associated with the development of bankruptcy prediction models from 1990 to 2024. Consequently, 180 works have been examined, encompassing more than 400 models. The review and analysis of bankruptcy prediction studies pertaining to the V4 were conducted by scrutinising the relevant scientific literature. In the study, we selected publications derived mostly from the Google Scholar and ResearchGate databases covering the period from Q1 1990 to Q1 2024. The Kruskal–Wallis test, a nonparametric ANOVA, was employed to analyse the ranks of the measurement values of the ratios. The test was derived from a sample including more than 200,000 companies throughout the period of 2006–2021 from the V4. The results indicate that statistical approaches remain the most prevalent; however, their accuracy is inferior to that of machine learning methods. The number of ratios incorporated in the V4 models fluctuates between three and eight indicators. Nonetheless, only a select few are frequently included in the models, including the total debt ratio (DR), equity ratio (ER), current liquidity ratio (CR), quick ratio (QR), return on assets (ROA) and return on equity (ROE). Thus far, no attempts have been made to utilise text analysis to assess the value of off-balance-sheet

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information for enterprises operating in the V4. It is noteworthy that, to date, no efforts have been undertaken in Hungary to publish the validation of any previously constructed models by independent academic researchers. The research was executed by specialists from each assessed V4 country, who had previously developed models for their respective countries. Studies published in both English and local languages (Czech, Hungarian, Polish, and Slovak) were considered. To the authors' knowledge, this is the inaugural comprehensive examination of models developed in the V4. We also checked the statistical significance of the values of the most used ratios in research and models among the V4 countries by using nonparametric ANOVA. Based on the results, we recommend verifying the accuracy of existing models using the most up-to-date large research database, and suggest checking the usefulness of text analysis for assessing the financial condition of companies.

Key words

model validation, financial and nonfinancial ratios, statistical methods, artificial intelligence methods, ANOVA.

Introduction

Enterprises in a market economy are perpetually evaluated by owners, suppliers, managers, business partners, and prospective investors. In developed countries, the Western market economy has functioned for a far longer duration than in post-communist economies, which transitioned to free market systems at a later stage. In this context, more approaches for evaluating enterprises have been constructed, particularly for advanced economies, where the operational history of businesses is significantly longer, resulting in better data accessibility.

Initially, financial ratio analysis was employed to evaluate the company's ratios to industry benchmarks throughout the 19th century. Subsequently, efforts were undertaken to identify ratios that exhibited certain capabilities, such as better predictive power (Fitzpatrick, 1932). As statistical methods evolved, novel approaches for evaluating organisations emerged, including univariate discriminant analysis (Beaver, 1966), multivariate discriminant analysis (Altman, 1968), and logit analysis (Ohlson, 1980). Alongside statistical approaches, further advancements included techniques rooted in artificial intelligence, such as neural networks (Messier Jr & Hansen, 1988), self-organising maps (Kohonen, 1997), and genetic algorithms (Varetto, 1998). In post-communist countries, including the Visegrad Group (V4), bankruptcy prediction models began to be developed only in the 1990s.

A multitude of reviews about models designed for developed markets has been utilised so far, which is, of course, a result of the aforementioned factors. The most significant include those by Kumar and Ravi (2007), Bellovary et al. (2007), and Ahmed et al. (2022). The first two date to 2007 and have each been cited over 1,000 times, while the newest, produced less than three years ago, has already received almost 250 citations. Bellovary et al. (2007) examined more than 170 studies on bankruptcy prediction from 1930 to 2007, detailing the prevalence of specific bankruptcy prediction methodologies, the quantity of indicators utilised in the research (enumerating the frequency of indicator occurrence in the models), whether the models underwent testing, and their accuracy in classification. Kumar and Ravi (2007) conducted a review of bankruptcy prediction in banks and enterprises from 1968 to 2005. The review included 128 publications, detailing the ratios, methodologies, samples, and dataset timelines for each study. Ahmed et al. (2022) examined 348 works related to artificial intelligence and machine learning in finance from 2011 to 2021, with a minority addressing bankruptcy prediction and credit risk assessment. They evaluated the most prolific and impactful countries, undertook citation analysis, identified the most pertinent academic sources, and recognised the most relevant authors. Identifying particular authors from the V4 in the offered works is challenging, as the initial models were developed in their respective native languages: Czech, Hungarian, Polish, and Slovak. Furthermore, several papers had not yet been indexed in scientometric databases and lacked unique DOI identifiers. This article seeks to address the highlighted research gap by providing a comprehensive assessment of journal articles concerning corporate bankruptcy prediction in the V4.

The paper is structured as follows. Section 2 reviews the literature on bankruptcy prediction related to the V4. Section 3 outlines the methodology. Section 4 presents the results. Section 5 contains the discussion, while Section 6 delineates conclusions and recommendations for future research.

1. Literature review

There are a few summary studies on bankruptcy prediction models developed for particular V4 countries. The inaugural review, including authors from the V4 countries (Alaka et al., 2018) was published in 2017. This research presents a comprehensive review of 49 journal articles published from 2010 to 2015. The authors provide a comprehensive overview of the literature employing prevalent methodologies for bankruptcy prediction, including multiple discriminant analysis (MDA), logistic regression (LR), neural networks (NN), support vector machines (SVM), rough sets (RST), case-based reasoning (CBR), decision trees (DT), and genetic algorithms (GA). Through a systematic review, they identify 13 essential criteria: accuracy, result transparency, nondeterminism, sample size, data dispersion, variable selection method, multicollinearity, variable types, variable relationships, assumptions imposed by tools, sample specificity/overfitting, updateability, and integration capability. The subsequent two studies by Kral et al. (2018) and Prusak (2018), have already focused on the V4 countries. Kral et al. (2018) succinctly outline selected studies on the models developed in Czechia, Hungary, Poland, and Slovakia. Prusak (2018) examines a far greater number of models developed over a broader array of countries, specifically focusing on Central and Eastern European nations. A far more comprehensive study of the models was conducted by Kovacova et al. (2019) The review considers 103 bankruptcy prediction models developed in the V4 from 1993 to 2018. The authors determined the quantity of prediction models in various countries, the methodologies employed for model development, the number of explanatory variables incorporated in the models, the most often utilized ratios inside the models, and conducted a cluster analysis. The subsequent work (Kristóf & Virág, 2020) focuses on the examination of models specifically developed for the Hungarian economy. The authors do a comprehensive examination of the models, including the year of inception, ratios, sample size, research techniques, and classification accuracy. One of the two most recent papers (Prusak & Karas, 2024) compares the status of bankruptcy prediction research among the V4 nations and in connection to worldwide trends, while also conducting a bibliometric analysis. The final study (Dasilas & Rigani, 2024) focuses on bankruptcy prediction models covering the period from 2012 to mid2023. The researchers examined 207 publications, evaluating the most prevalent machine learning algorithms employed, data samples, accuracy, the most cited paper, and leading journals. They concentrate on the global context rather than only on the V4 countries.

Among the review studies on bankruptcy prediction models, only four pertain to all the V4 countries. Only two of them, Kral et al. (2018) and Prusak (2018), engaged with the authors of the works without doing a thorough analysis of the offered models. Conversely, two more studies Kovacova et al. (2019) and Prusak and Karas (2024) exclude several publications from the examined countries, neglecting some significant and highly referenced articles. This is attributable to the publication of some works in the local language of specific countries and the initial absence of particular DOI codes, rendering them inaccessible in various databases such as Scopus and Web of Science. Ultimately, no research was conducted by specialists from particular countries (four authors from different countries of the V4); there were simply fewer contributors, and most frequently, they were experts pertaining to their own countries. Consequently, specialists from each V4 country convened to compile this comprehensive analysis of bankruptcy prediction models for the period 1990 to 2024.

2. Methodology

The objective of the research is to identify the principal variables pertinent to bankruptcy prediction or financial distress studies across the V4, comprising Czechia, Hungary, Poland, and Slovakia. Consequently, the review and analysis of bankruptcy prediction studies pertaining to the V4 were conducted by examining the relevant scientific literature. In the study, we selected publications derived mostly from the Google Scholar and ResearchGate databases covering the period from Q1 1990 to Q1 2024. The research was executed by specialists from each assessed V4 country, who had previously developed models for their respective countries. Studies published in both English and local languages (Czech, Hungarian, Polish, and Slovak) were considered. To the authors' knowledge, this is the inaugural such huge comprehensive examination of models developed in the V4.

The article examines the models, their accuracy, the methodology used, the research period, the sample size, as well as the indicators present in these models and those considered in the studies. This comprehensive study of indicators facilitates the identification of the most prevalent indicators utilised in empirical research and final models. First, the models were individually examined for each V4 country. Second, the efficacy of the models was assessed based on a literature review. Third, the indicators present in both the studies and the models were examined. Finally, a comprehensive analysis was conducted. In that section, we analyse the most frequently used ratios in research and models based on the sample retrieved from the EMIS database (EMIS stands for Emerging Markets Information Service, a Euromoney Institutional Investor Company, www.emis.com). The sample consists of more than 200,000 companies in the period of 2006–2021, with more than 1,000,000 company-year observations used in the sample and covers four countries: Czechia, Hungary, Poland, and Slovakia. We use non-parametric analysis of variance (ANOVA), the so-called Kruskal-Wallis test. The ANOVA is a frequently used method for analysing dissimilarities between the averages/medians of two or more groups. In this particular case, differences between the values of each ratio in four countries are checked.

The Kruskal–Wallis test, as a nonparametric ANOVA, does not require a normal distribution of the values of the ratios. Similar to other nonparametric tests, it is carried out on the ranks of the measurement values of the ratios. A rank of 1 is assigned to the smallest value, a rank of 2 is assigned to the second smallest, etc. The sum of the ranks, R_i, is computed for each group, i (i = 1, 2 ,…, C), of size n_i, and then the test statistic, H, is computed (Kruskal & Wallis, 1952). The *H* is approximately Chi-squared-distributed, with the degrees of freedom equal to the number of groups, C, minus 1.

$$H = \frac{12}{N \cdot (N+1)} \sum_{i=1}^{C} \frac{R_i^2}{n_i} - 3(N+1) \tag{1}$$

where C is the number of groups; n_i is the number of observations in the ith group; $N = \sum n_i$ is the number of observations in all groups combined; and R_i is the sum of the i-th group.

The following hypotheses were tested:

Hypothesis 0 (H0). The different samples in the comparison were drawn from the same distribution, or from distributions with the same median.

Hypothesis 1 (H1). The different samples in the comparison were not drawn from the same distribution, or from distributions with the same median.

The analysis of the Kruskal–Wallis test is very similar to the abovementioned ANOVA. The test is based on ranks instead of means. If the null hypothesis was rejected, various comparisons of the average ranks for all groups were carried out. The comparisons are computed as the post hoc analysis of the average ranks of all pairs of groups (Siegel & Castellan, 1988). The z values for each comparison between groups u and v can be calculated as:

$$z_{u,v} = \frac{|\bar{R}_u - \bar{R}_v|}{\sqrt{\frac{N(N+1)}{12} \cdot \left(\frac{1}{n_u} + \frac{1}{n_v}\right)}} \quad (2)$$

where $\bar{R}$ indicates the mean ranks for the two groups, and n_u and n_v represent the number of observations in the two groups (u and v, respectively).

Each company is assigned to only one group (country), which means that samples are independent. The number of companies included in each country differed, and consisted of 8,315 companies for Czechia, 8,857 companies for Slovakia, 31,241 companies for Hungary, and 73,747 companies for Poland. The number of companies in different years also differs.

The subsequent research questions have been established to facilitate the study:

RQ1: What methods are applied to predict the bankruptcy of firms within the V4?

RQ2: Has the model's accuracy been validated?

RQ3: Do the researchers' analyses of individual model accuracy align with the accuracy reported by the model authors?

RQ4: What are the most commonly used indicators in models and studies in the V4?

RQ5: Are the differences between the values of the selected ratios between countries statistically significant?

RQ6: What is the number of indicators utilised in the study and models across the V4?

RQ7: What sample sizes were utilised to develop the models?

RQ8: In which journals do the authors of the models disseminate their research?

3. Research results

3.1 Analysis of Bankruptcy Prediction Models in the V4 Group

The analysis encompassed four countries, namely Czechia, Hungary, Poland, and Slovakia, together with the V4 group as a whole. Table 1 features 21 papers pertaining to Czechia, Table 2 enumerates 31 articles for Hungary, Table 3 displays 49 articles for Poland, Table 4 encompasses 39 articles for Slovakia, and Table 5 presents 7 articles for the V4 as a whole from the first quarter of 1990 to the first quarter of 2024. A total of 147 articles were included in the analysis, 33% for Poland 27% for Slovakia, 21% for Hungary,14% for Czech, and 5% for the V4.

3.2 Analysis of Models in Czechia

Table 1 contains 21 publications in which a total of 73 models were developed and published. The history of bankruptcy prediction models began with the IN family of models expanding from 1995 to 2005, providing the names to the models – IN95, IN99, IN01, and IN05. The IN05 model was the first model presented at a scientific conference in 2005 (Neumaier & Neumaierová, 2005).

Table 1. Bankruptcy prediction models constructed for the Czech economy.

Model	No. of methods	Best method	Accuracy	Sample size	Period	Sector	No. of ratios	Selection criteria	No. of ratios in model
Neumaier and Neumaierová (2005)	1 (2)	MDA	97 % (B) / 92 % (A)	1,526	2005	M	nd	nd	5
Dvořáček et al. (2008)	1(1)	MDA	70% (B)/ 100% (A)	73	nd	MINI	8	BTH	8
Jakubík and Teplý (2011)	1(1)	LR	80.41 % (Gini)	31,612	1993-2005	nd	22	STW	7
Dvořáček et al. (2012a)	3(3)	ANN	90 % (A) / 100 % (B)	186	1996-2010	nd	8	FS	8
Dvořáček et al. (2012b)	1(4)	MDA	85 % (A) / 92% (B)	170	1997-2008	M, C, AG, SE	10	nd	5-8 (7)
Valecký and Slivková (2012)	1(1)	LR	0,8625 (AUC)	400	2008	nd	19	STW	4
Kalouda and Vaníček (2013)	1(2)	MDA	0,853 (AUC)	538,162	nd	nd	39	DP	8
Karas and Režňáková (2013)	1(1)	MDA	78 % (A) / 92 % (B)	207	2007-2010	M	38	STW	3
Karas and Režňáková (2014)	2(5)	Boosted trees	92 % (A) / 96 % (B)	1,908	2004-2011	M	38	RI	5

Bemš et al. (2015)	5(18)	magic square	30 % (Gini)	3,120	nd	nd	5	GINI	5
Machek et al. (2015)	2(2)	MDA	78%	3,158	nd	CB	5	ALV	5
Vochozka et al. (2015a)	1(1)	LR	92%	12,930	2003-2012	TR	nd	SIG	12
Vochozka et al. (2015b)	1(6)	ANN	94%	15,189	2003-2013	C	100	nd	nd
Němec and Pavlík (2016)	1(1)	LR	84%	241,38	2005-2013	G	30	UA	6
Slavíček and Kuběnka (2016)	1(4)	LR	0,94 (AUC)	33	2013	C	12	MA, AAR	4
Vochozka et al. (2016)	1(1)	ANN	0,963 (AUC)	67,000	2003-2013	M	91	FS	91
Karas and Režňáková (2017)	1(2)	CART	62% (A) / 92 % (B)	1,540	2011-2014	C	29	CART	5
Vochozka (2017)	1(10)	MLP	94.40%	65,536	2008-2014	C	90	NN	6
Karas and Režňáková (2018)	1(6)	MDA	0,889 (AUC)	1,355	2011-2014	C	28	STW	5
Karas and Srbová (2019)	1(1)	MDA	77,28 % (A) / 86 % (B)	4,420	2011-2015	C	35	STW	4
Karas and Režňáková (2020)	3 (3)	CART + PCA + LR	0,82 (AUC)	4,350	2013-2018	M	31	PCA + CART	6

Note: AAR – all areas of group of ratios, AG – agribusiness, ALV – variables from Altman's model, BTH – Based theory, C – construction, CB – Cultural business, CART - Classification And Regression Trees, DP- discrimination power, FS – full set, G – general, GINI- Gini coefficient, M – manufacturing, MA – maximum of accuracy, MINI – mining, nd – no data, PCA – principal component analysis, RI – relative importance, SE – service, SIG – significance test, STW stepwise, TR- Transport, UA – univariate analysis.

Source: Neumaier and Neumaierová (2005), Dvořáček et al. (2008), Jakubík and Teplý (2011), Dvořáček et al. (2012a), Dvořáček et al. (2012b) Valecký and Slivková (2012), Kalouda and Vaníček (2013), Karas and Režňáková (2013), Karas and Režňáková (2014), Bemš et al. (2015), Machek et al. (2015), Vochozka et al. (2015a), Vochozka et al. (2015b), Němec and Pavlík (2016), Slavíček and Kuběnka (2016), Vochozka et al. (2016), Karas and Režňáková (2017), Vochozka (2017), Karas and Režňáková (2018), Karas and Srbová (2019), Karas and Režňáková (2020).

From 2005 to 2019, there were 21 separate articles published proposing new or updated bankruptcy models, particularly created for Czech companies. Most of the models (81%) were published between 2012 and 2018. The models vary in several dimensions, including the classification algorithm utilised, the variable selection methodology, and the approach to accuracy assessment. Methodologically, the predominant technique for model development was MDA at 41%, followed by the LR (23%) and NN (14%). Approximately one third of these models (31%) are designed as generic models, indicating that they do not concentrate on a specific industry sector. The industry-specific models predominantly focused on construction enterprises (27.3% of cases) and manufacturing enterprises (22.7% of cases). Due to the varied accuracy metrics employed by different authors, it is challenging to ascertain which method achieved the maximum accuracy in the context of Czech models. Five of the nine studies utilising the MDA technique employ genuine positive rate metrics, with the rate for bankrupt firms ranging from 70% to 97%, and for nonbankrupt enterprises from 78% to 100%. It is important to note that not all research references these figures as out-of-sample data. Two studies report Area Under Curve (AUC) values of 0.853 and 0.889, while the other two provide overall accuracy of 78% and 84.8%. The authors employed the logit technique, utilising AUC measurements of 0.8625 and 0.94, alongside overall accuracy and a Gini coefficient (GINI) of 80.4%, which corresponds to an AUC of 0.9205.

The models have the characteristic of often analysing a relatively short time frame, occasionally limited to a single period (Neumaier & Neumaierová, 2005; Valecký & Slivková, 2012; Slavíček & Kuběnka, 2016), while for four models, the particular time period was not disclosed. The most extended analysed period was 14 years for model (Dvořáček et al., 2012a) and 12 years for model (Jakubík & Teplý, 2011). The average duration of the analysed period is 6.1 years. Another characteristic that distinguishes the models is the methodology employed to obtain the set of model variables. In one third of the analysed models, there was no reduction in the set of ratios established. In other instances, the array of possible ratios was not elaborated upon and was only referenced, for example, as 100 corporate characteristics. The analysis of financial ratios varies from 10 in the case of the Dvořáček et al. (2012b) model to 39 in the Kalouda and Vaníček (2013) model, contingent upon the supplied list of potential variables. Some authors, for example Vochozka and Rowland (2015) and Vochozka et al. (2016) utilised artificial neural networks to manage a substantial number of variables and incorporated 91 or about 100 firm features.

3.2 Analysis of Models in Hungary

A total of 121 models has been developed and published within the context of the 31 Hungarian references. Only conventional statistical techniques (MDA, LR) were used in 16 scholarly articles, representing 51.6% of the sources (Table 2).

Table 2. Bankruptcy prediction models constructed for the Hungarian economy.

Model	No. of methods	Best method	Accuracy	Sample size	Period	Sector	No. of ratios	Selection criteria	No. of ratios in model
Hajdu and Virág (2001)	2 (2)	LR	82%	154	1990-1991	G	16	STW	5
Virág and Kristóf (2005)	3 (8)	NN	86%	154	1990-1991	G	16	BAC	16
Virág and Kristóf (2006)	4 (4)	NN	87%	154	1990-1991	G	16	BAC	16
Kristóf	4 (4)	NN	84%	504	2004-2005	G	31	PCA, EPR	5
Virág and Kristóf (2009)	1 (1)	LR	94%	100	2004	G	31	PROXSCAL, STW	31
Bozsik (2011)	3 (5)	BF-ANN-DT	84%	400	2009	G	16	DT, RRP	16
Kristóf and Virág (2012)	4 (12)	NN	94%	504	2004-2005	G	31	PCA, CHAID, PRI	15
Virág and Nyitrai (2013)	2 (2)	SVM	89%	156	1990-1991	G	17	t-test	10
Bareith et al. (2014)	1 (1)	NN	85%	8,004	2002-2012	G	10	PRI	8
Ékes and Koloszár (2014)	4 (4)	NN	73%	148	2011	G	31	BAC	31
Nyitrai (2014a)	1 (1)	CHAID	78%	1,000	2009-2012	G	17	CHS, DT	7
Nyitrai (2014b)	1 (1)	C4.5	76%	1,000	2004-2012	G	17	IG, DT	11
Virág and Nyitrai (2014a)	3 (3)	RST	89%	156	1990-1991	G	17	t-test, REP	5
Virág and Nyitrai (2014b)	1 (7)	C4.5	83%	976	2001-2012	G	17	BA, DT	17
Felföldi-Szűcs (2015)	1 (1)	LR	70%	905	2008	G	41	STW	12
Nyitrai (2015)	1 (1)	KNN	80%	1,000	2001-2012	G	17	t-test	7
Inzelt et al. (2016)	1 (1)	LR	86%	368,328	1999-2013	G	29	BA, DT, STT	5
Nyitrai (2017)	1(1)	LR	90%	2,094	2009-2015	G	20	BO, STW	11
Nyitrai and Virág (2017b)	1(4)	LR	81%	1,354	2001-2014	G	18	STW	12
Nyitrai and Virág (2017a)	1(2)	LR	91%	1,542	2001-2014	G	18	STW	11
Kristóf (2018)	4(4)	NN	82	1,828	2015-2016	G	28	PCA, LMA	28
Nyitrai (2018)	1(16)	LR	91%	2,614	2007-2015	G	25	STW	16
Sütő (2018)	2(2)	LR	83%	86	2009-2012	RTC	22	STW	8
Nyitrai (2019a)	1(5)	MDA	89%	2,098	2007-2016	G	20	CHAID, STW	8
Nyitrai (2019b)	4(4)	MDA	83%	3,370	2001-2015	G	17	CHAID, STW	6
Nyitrai and Virág (2019)	5(15)	MDA	87%	2,996	2007-2016	G	20	CHAID, STW	12
Szenes and Dabi (2020)	1(1)	LR	80%	286,445	2006– 2017	G	27	WOE, GINI, COR	7
Horváth (2021)	1(1)	LR	78%	63,772	2007-2017	G	22	LASSO	15
Ágoston (2022)	6(6)	RF	84%	208	2014-2018	G	8	PRI, DT	8
Márton et al. (2023)	1(1)	LR	78%	190,982	2017-2018	G	26	CHAID, STW	9
Szántó (2023)	1(1)	LR	86%	1,677	2013-2021	C	19	STW	7

Note: BA – bagging, BAC – backpropagation, BO – bootstrap, CHS chi-squared, COR - correlation analysis, DT- decision trees, EPR - exhaustive prune, IG – information gain, LMA - Levenberg-Marquard algorithm, PRI - predictor importance, REP - recursive partitioning, RRP reduced error pruning, RTC - retail trade companies, STT – stability test, WOE - weight of evidence

Source: Hajdu and Virág (2001), Virág and Kristóf (2005), Virág and Kristóf (2006), Kristóf (2008), Virág and Kristóf (2009), Bozsik (2011), Kristóf and Virág (2012), Virág and Nyitrai (2013), Bareith et al. (2014), Ékes and Koloszár (2014), Nyitrai (2014a), Nyitrai (2014b), Virág and Nyitrai (2014a), Virág and Nyitrai (2014b), Felföldi-Szűcs (2015), Nyitrai (2015), Inzelt et al. (2016), Nyitrai (2017), Nyitrai and Virág (2017b), Nyitrai and Virág (2017a), Kristóf (2018), Nyitrai (2018), Sütő (2018), Nyitrai (2019a), Nyitrai (2019b), Nyitrai and Virág (2019), Szenes and Dabi (2020), Horváth (2021), Ágoston (2022), Márton et al. (2023), Szántó (2023).

The remaining articles (48.4%) employed at least one machine learning (ML) technique. The inaugural ML-based model was published in Hungary in 2005. In Hungary, the Bankruptcy Act introduced the foundations to statistically analyse bankruptcy prediction in the early 1990s. Over the years, significant progress has been made in Hungarian literature and the practice of bankruptcy prediction. The first Hungarian bankruptcy models were developed using financial data from 1990 and 1991, applying MDA and LR. Out of 154 industrial enterprises, 77 were financially stable and 77 experienced insolvencies in 1992. The models were first published in Hungarian and later in English in 2001 (Hajdu & Virág, 2001). Researchers subsequently experimented with various architectures to construct NN-based models on the same database, resulting in a four-layer backpropagation network that demonstrated superior performance compared to the previous LR model (Virág & Kristóf, 2005). A more complex empirical study on the same database by employing the industrial mean relative ratios again found that NN outperformed traditional methods in terms of performance (Virág & Kristóf, 2006).

In 2008, a more recent database with a broader set of variables was compiled, and four techniques were applied. The NN model had the highest performance, with an Area Under the Receiver Operating Characteristic Curve (AUROC) of 0.84 (Kristóf, 2008). A LR model was developed one year later based on reduced-dimensional coordinates, resulting in exceptional classification accuracy, after transforming differences between solvent and insolvent observations into coordinates using Mahalanobis distance (MD) (Virág & Kristóf, 2009).

Bozsik (2011) demonstrated the effectiveness of integrating DT with NN by applying single-layer perceptron networks to C4.5 decision trees. The optimised brute force models achieved an accuracy rate of 84 percent in classification. A similar comparative empirical research article used a sample of 504 Hungarian enterprises to analyse the positive effect of chi-squared automatic interaction detection (CHAID) on model performance. Results demonstrated that the discretised variables substantially improved LR and NN models' performance (Kristóf & Virág, 2012).

An empirical examination by Virág and Nyitrai (2013) used SVM on a Hungarian corporate database, demonstrating superior classification performance compared to the benchmark NN model. Authors later applied the RST method to further experiment with ML techniques on Hungarian enterprises (Virág & Nyitrai, 2014a). They aimed to determine if sacrificing model interpretability for greater accuracy was justified. The results showed that RST, using clear 'if-then' rules, yielded comparable results to SVM, ensuring the balance between comprehensibility and effectiveness. The K-nearest neighbours (KNN) was used for Hungarian bankruptcy prediction in a study using a balanced sample of 1,000 observations (Nyitrai, 2015). The models were created using various k values, distance definitions, and variables from 1, 2, and 3 years prior to bankruptcy. The multi-period variables yielded the most favourable result, outperforming the one-year-previous model. A comparable study with CHAID also found similar conclusions (Nyitrai, 2014a). In a subsequent study using CBR as a comparative approach to KNN, 1,828 Hungarian micro-enterprises were analysed (Kristóf, 2018). Principal component analysis (PCA) was used to ensure independent input variables, and the nearest neighbours were identified using the reduced dimensionality tree (RDT) technique. The CBR model had higher classification accuracy than the DT and LR models, but lower accuracy than the benchmark NN model. An empirical research by (Virág & Nyitrai, 2014b) examined the effectiveness of ensemble approaches in analysing financial ratios of Hungarian enterprises from 2001 to 2012. The bagging technique was found to be the best solution. Results demonstrated that dynamic variables positively impacted model performance, but industrial mean ratios did not improve it. Other results also indicated that dynamization improves predictive power. By using indicator variables, models with minimum and maximum values from previous periods showed enhanced classification accuracy (Nyitrai, 2019b). By employing ten-fold cross-validation, all models demonstrated that incorporating dynamised variables led to enhanced classification accuracy in comparison to models built just using the original static variables. Generating category factors based on node number in CHAID also improved prediction capability compared to using original data as input variables (Nyitrai, 2019a). A study analysing the financial ratios of 1,542 Hungarian enterprises from 2001 to 2014 found that AUROC showed stronger model performance when considering more historical years. For companies less than 10 years old, including all available years of data was beneficial, while using the most recent 10 years of data yielded the greatest model performance (Nyitrai & Virág, 2017b). Another study also corroborated the findings on a different sample containing 1,354 companies (Nyitrai & Virág, 2017a). Researchers in Bareith et al. (2014) used a single hidden layer NN to predict insolvency of enterprises. Due to the repercussions of the financial crisis, the database was divided into two economic periods, 2002-2008 and 2009-2012, analysing financial ratios from three historical years. The model performed better from 2002 to 2008, indicating its effectiveness in predicting insolvency. Nyitrai (2018) conducted a study to analyse the effects of firm size and industry on bankruptcy models. They used a sample of data from 2007-2015, consisting of 2,614 Hungarian enterprises. The LR models demonstrated that both business size and industry had a significant impact on the design and performance of bankruptcy models. Nyitrai (2017) conducted comprehensive research on the effect of linking stock balance sheet items to flow profit-and-loss statement items on the accuracy of bankruptcy prediction models. Nyitrai and Virág (2019) evaluated the impact of handling outliers on model performance using different approaches. The study determined that the use of CHAID for categorisation was more successful in managing outliers compared to the methods of coercing based on external percentiles or the mean of multiple standard deviations. A similar study conducted by Szántó (2023) investigated the effects of various outlier handling methods on model performance using a database of Hungarian construction companies. The most favourable approach in this research was the nearest neighbour's imputation.

A LR model was developed for companies in the retail sales sector residing in non-specialised stores in the Northern Great Plain region (Sütő, 2018). A study on Hungarian small and medium enterprises (SME) demonstrated that bankruptcy models for large corporations cannot be applied to SMEs with different financial behaviours (Ékes & Koloszár, 2014). Alternatively, the best model was found using NN. Research on firm insolvency using ML methods in Hungary's Pecs and Budapest regions found the RF model had the highest predictive power to assess bankruptcy risks (Ágoston, 2022). A comparative study on corporate credit risk models in Hungary found that incorporating behavioural and non-financial characteristics improved discriminatory power, outperforming models based solely on financial ratios (Felföldi-Szűcs, 2015).

Four published Hungarian corporate financial distress models were based on a relatively large database. Three of these models were developed by researchers from the National Bank of Hungary. The study of Inzelt et al. (2016) aimed to develop a supervisory corporate default model to facilitate the effective monitoring of Hungarian companies in the banking sector. The modelling database from the period 1999-2013 consisted of 368,328 companies. Horváth (2021) conducted empirical research using data from 63,772 companies to support credit risk stress testing and evaluate the susceptibility of corporate lenders based on individual client defaults that occurred from 2007 to 2017. For the purpose of establishing a standard model for evaluating internal corporate rating systems employed by Hungarian banks, Szenes and Dabi (2020) introduced a comprehensive and widely applicable benchmark model. This model was developed using historical data from 286,445 companies. A team of researchers Márton et al. (2023) created a bankruptcy model that evaluated the level of risk associated with Hungarian companies during the COVID-19 era. They utilised a dataset containing 190,982 records of corporate financial data.

Out of the total number of articles, 22 (71.0%) were published in various Hungarian journals, primarily in prestigious publication outlets within Hungary. Only 9 papers (29.0% of the total) on Hungarian bankruptcy models have been published in English scientific journals.

3.3 Analysis of models in Poland

A comprehensive examination of Table 3 reveals that a total of 352 models were constructed for the Polish economy, relying exclusively on 49 articles. By incorporating the models presented in monographs and at conferences, the number of models would be significantly increased.

In Poland during the early 1990s and 2000s, the construction of statistical models (SM) was limited to two main approaches: MDA and LR models. In recent years, there has been a proliferation of advanced models, such as the fuzzy logic model (FL), into the academic literature. In light of the growing prevalence of ML and artificial intelligence (AI) models, it is noteworthy that 65% of articles employed MDA, while 45% utilised LR. Furthermore, the decline in the utilisation of MDA and LR signifies a reduction in their proportion in the overall number of models generated. On average, statistical models account for 42% of the constructed models, with 82 models for MDA and 78 models for LR. In contrast, ML and AI techniques are present in 43% of the documented articles, with a total of over 210 models developed, representing 57% of the overall models. Multimethod analysis articles encompass a range of statistical, ML, and AI techniques, wherein SM are juxtaposed with models derived from more advanced methodologies. Furthermore, a majority of the articles (53%) incorporated models that encompassed multiple sectors, while a smaller proportion (22%) focused solely on the manufacturing sector. Correlation analysis (COR) was the most commonly employed criterion for indicator selection, as evidenced by its usage in 13 articles. The stepwise (STW) method was utilised in 10 articles, while Wilks' lambda (W-L) statistic was employed in 7 articles. Furthermore, these criteria are primarily employed in the context of SM. The assumptions that ML and AI models must satisfy are comparatively fewer than those of SM. The levels of accuracy exhibited by the models presented in the articles differ across individual works. Both the minimum and maximum values are observed for MDA, with numerical values of 69% and 100%, respectively. It is important to note that the efficacy of SM can be readily validated, such as through the examination of existing literature. These findings will be presented in the subsequent section of the article.

Table 3. Bankruptcy prediction models constructed for the Polish economy.

Model	No. of methods	Best method	Accuracy	Sample size	Period	Sector	No. of ratios	Selection criteria	No. of ratios in model
Mączyńska (1994)	1 (1)	DA	-	nd	-	nd	6	ED	6
Pogodzińska and Sojak (1995)	1 (1)	DA	80%	10	1993	G	2	ED	2
Tarczyński (1996)	1 (1)	DA	69%	42	1995	G	14	nd	14
Tarczyński (1998)	1 (1)	DA	69%	42	1995	G	14	nd	14
Zawadzki and Babis (1998)	1 (1)	DA	100%	17	nd	RRSRF	40	COR, ED, STW	6
Wierzba (2000)	1 (1)	DA	92%	48	1995-1998	G	12	COR, STW	4
Appenzeller (2001)	1 (3)	DA	94%	56	1991-1997	G	16	S-W; SKC; K-S; W-L	4-7
Hołda (2001)	1 (1)	DA	93%	80	1993-1996	G	13	ED	5
Sojak and Stawicki (2001)	1 (3)	DA	93%	58	1998	G	20	k-means, WM, FAA	3-7
Appenzeller and Szarzec (2004)	1 (2)	DA	88%	68	2000-2002	G	19	COE R, STW	5-6
Gruszczyński (2004)	1 (4)	LR	91%	200	1995-1997	G	17	COR	2-3
Hamrol et al. (2004)	1 (1)	DA	96%	100	1999-2002	G	31	COE R, COR, W-L	4
Sojak and Konieczka (2004)	1 (4)	DA	97%	54	1996-2000	SR	24	WM	8-9
Wędzki (2005a)	1 (6)	LR	88%	2,300	2000-2003	G, C	21	S-W, UMW, STW	2-7
Wędzki (2005b)	1 (8)	LR	79%	80	2000-2003	G	20	COR	2-7
Wędzki (2005c)	1 (8)	LR	78%	80	2000-2003	G	20	CSV, KC, STW, COR	2-7
Mączyńska and Zawadzki (2006)	1 (7)	DA	97%	80	1997-2002	G	42	DIFM, DIFI, TIV, MD, COR, W-L	4-11
Korol (2010a)	4(24)	DA	96%	132	2000-2005	M, SE	28	nd	14
Korol (2010b)	7(52)	SSN REC	94%	185	2000-2005	M, SE	28	COR	28
Dębkowska (2012)	3(3)	CT	97%	68	2009	G	17	HM, COR	7
Pisula (2012a)	1(2)	LR	91	205	2004-2012	L	24	IV, GINI, Vcramer	6-20
Pisula (2012b)	3(15)	NN	92%	207	2007-2010	L	26	COR	3-26
Ptak-Chmielewska (2012)	3(3)	LR	85%	1,536	2002-2011	G	21	COR	9
Wędzki (2012)	1(11)	LR	83%	76	2001-2003	G	nd	STW	8
Dębkowska (2013)	2(12)	CT	97%	120	2010	G	14	HM, COR	10
Gąska (2013)	2(3)	SVM	90%	18	2008-2012	G	17	AUC	4
Korol (2013)	3(6)	CT	96%	185	2000– 2007	M, SE	14	nd	3
Pisula et al. (2013)	3(8)	MLP	94%	66	nd	L	28	WM	6
Waszkowski (2013)	1(1)	L	78%	36	2010	G	20	COR	5
Balina and Juszczyk (2014)	3(3)	DA	93%	60	2007-2010	ICRTS	42	COR, STW, t-test	2-4
Juszczyk and Balina (2014)	1(4)	DA	91%	180	2007-2010	C, W, RTG, G	42	COR, t-test, NOR, MEV	3-4
Gąska (2015)	5(42)	SVM	76%	94	2008-2014	G	17	STD, BO, WMW	3-5
Pisula et al. (2015)	2(8)	MLP	95%	66	nd	L	28	IV, GINI, Vcramer	26
Rusiecki and Białek-Jaworska (2015)	2(3)	DA	98%	142	2009-2014	C	38	COR, J-B, SW	4-7
Wojnar (2015)	2(8)	DA, LR	92%	140	2012-2013	C, M	38	t-test, W-L	2-6
Zięba et al. (2016)	16(16)	EXGB	96%	10,700	2000-2012	M	64	DIS 0	64
Pisula (2017)	6(6)	NNet	98%	144	2008-2014	M	11	SUM, VCramer, IV	11

Pawełek and Grochowina (2017)	1(28)	Bagging	79%	7,223	2013-2015	M	16	RF	4
Wójcicka (2017)	2(6)	NN	97%	nd	2009-2015	C, M, T	25	DA	7-10
Balina (2018)	3(3)	DA	87%	60	2009-2013	W F M	42	COR, t-test	3-4
Durica et al. (2019a)	1(2)	CT	98%	29,000	2016-2017	G	37	ROC	3
Jaki and Ćwięk (2020)	1(2)	DA	99%	44	2010-2015	C	20	COR, K-S, S-W, W-L	7-12
Pawełek et al. (2020)	4(32)	NN	81%	246	2005-2010	M	39	STW	3
Pisula (2020)	1(1)	GBM	99%	3,679	2018	G	22	GA	2-19
Tomczak (2020)	2(2)	DA	92%	10,700	2000-2012	M	64	K-S test, t-test, COR, W-L, STW	5
Geise et al. (2021)	1(1)	LR	89%	3,641	2017	C	17	z-test	7-17
Noga and Adamowicz (2021)	1(1)	DA	89%	135	2006-2012	WO	15	COR, W-L	5
Ptak-Chmielewska (2021)	2(2)	SVM	72%	806	2008-2010	G	21	t-test, CHS, COR	9
Kokczyński (2023)	1(10)	DA	75%	56	2017-2019	G	32	COR, STW, ED	5

Note: COE coefficient, CSV - cumulative share of variance, DIFI - distributions of indicators, DIFM difference of means, DIS - distribution, ED- expert decision, FAA - factor analysis, GA - genetic algorithms, HM - Hellwig's method, ICRTS - international commercial road transport sector, IV- Information Value, J-B - J-B Jarque-Bera, KC - Kaiser's criterion, K-S- Kolmogorov–Smirnov test, MD - Mahalanobis distance, MEV - multicollinearity of explanatory variables, NOR - normality test, RF – random forest, RRSRF - railway rolling stock repair facilities, SKC - Skewness and Kurtosis Coefficients, STD - Standardization, SUM - Symmetrical Uncertainty measure, S-W Shapiro–Wilk test, T – trade sector, TIV - trend in indicator values, UMW - Manna-Whitney, W-L - Wilks' Lambda test, WM- Ward method.

Source: Mączyńska (1994), Pogodzińska and Sojak (1995), Tarczyński (1996), Tarczyński (1998), Zawadzki and Babis (1998), Wierzba (2000), Appenzeller (2001), Hołda (2001), Sojak and Stawicki (2001), Appenzeller and Szarzec (2004), Gruszczyński (2004), Hamrol et al. (2004), Sojak and Konieczka (2004), Wędzki (2005a), Wędzki (2005b), Wędzki (2005c), Mączyńska and Zawadzki (2006), Korol (2010a), Korol (2010b), Dębkowska (2012), Pisula (2012a), Pisula (2012b), Ptak-Chmielewska (2012), Wędzki (2012), Dębkowska (2013), Gąska (2013), Korol (2013), Pisula et al. (2013), Waszkowski (2013), Balina and Juszczyk (2014), Juszczyk and Balina (2014), Gąska (2015), Pisula et al. (2015), Rusiecki and Białek-Jaworska (2015), Wojnar (2015), Zięba et al. (2016), Pisula (2017), Pawełek and Grochowina (2017), Wójcicka (2017), Balina (2018), Durica, et al. (2019a), Jaki and Ćwięk (2020), Pawełek et al. (2020), Pisula (2020), Tomczak (2020), Geise et al. (2021), Noga and Adamowicz (2021), Ptak-Chmielewska (2021), Kokczyński (2023).

Over 20 distinct methodologies were employed in the construction of bankruptcy prediction models across the 49 articles under analysis. The study of Zięba et al. (2016) employed the highest number of methods, totalling 16. The researchers considered the following methodologies: MDA; multilayer perceptron with a hidden layer (MLP); decision rules inducer (JRip); cost-sensitive variation of JRip (CJRip); decision tree model (J48); cost-sensitive variation of J48 (CJ48); LR; cost-sensitive variation of LR (CLR); adaBoost (AB); AdaCost (AC); SVM; cost-sensitive SVM (CSVM); random forest (RF); boosted trees trained with extreme gradient boosting (XGB); only the last tree of the ensemble of boosted trees, i.e., f K, trained with the Algorithm 1 (XGBE); ensemble of boosted trees trained with the Algorithm 1 (EXGB). The best performing models were derived from EXGB, achieving an accuracy rate of 96%. The level of accuracy was attained through the utilisation of a substantial research sample comprising nearly 11,000 manufacturing companies, accounting for the second most extensive research sample among the models outlined in Table 3. The dataset exhibited an imbalance, as only 700 out of the 11,000 companies were classified as bankrupt. The researchers employed the AUROC to assess the performance of the models. Additionally, they examined the quality of different training parameter configurations using a 10-fold cross-validation methodology for each model. Given the extensive number of ratios examined in the research, surpassing 60, it is noteworthy that the work of Durica et al. (2019a) encompasses the largest research sample among the Polish cases. The sample comprised nearly 29,000 companies operating across various sectors. CART and CHAID models were developed using classification trees (CT) as the structural basis. The receiver operating characteristic (ROC) curve was employed to evaluate the precision of the models at a level of accuracy of 98%. In contrast, the study conducted by Korol (2010b) offered the most extensive collection of models. The author developed a total of 52 models utilising seven distinct research methodologies, namely recurrent artificial neural network (SSN REC), one-way multi-layer artificial neural network (SSN MLP), artificial neural network based on genetic algorithms (SSN GA), artificial neural network with radial basis functions (SSN RBF), self-organising map (SOM), SVM, and FL. The predictive accuracy of the best model was 94%.

It is noteworthy that the initial publications on models developed for the Polish economy were solely written in the native language. However, in subsequent years, particularly at the onset of the 21st century (Appenzeller, 2001), the authors commenced publishing articles in English. This corresponds to the proportion of articles written in Polish, which accounts for nearly 60%, while English content comprises only 40% of the articles. Furthermore, this is pertinent to the scholarly journals in which the articles were published. In Poland, the availability of English-language journals or Polish journals that permitted the publication of articles in English was limited. Over the course of time, an increasing number of these journals were established, with authors commencing to select not only local publication outlets but also international journals such as International Advances in Economic Research (Gruszczyński, 2004), Economic Modelling (Korol, 2013) or Expert Systems with Applications (Zięba et al., 2016). Nevertheless, a limited number of such works remain within the 40% corpus of English-language articles.

3.4 Analysis of Models in Slovakia

A total of 39 studies on bankruptcy prediction were evaluated, encompassing 160 models, as published by Slovak authors (Table 4).

Table 4. Bankruptcy prediction models constructed for the Slovak economy.

Model	No. of methods	Best method	Accuracy	Sample size	Period	Sector	No. of ratios	Selection criteria	No. of ratios in model
Chrastinová (1998)	1(1)	DA	96%	1,123	nd	AG	nd	nd	5
Zalai (2000)	1(2)	DA	nd	160	1994-1997	G	72	STW	8
Hiadlovský and Kráľ (2005)	1(1)	DA	87%	42	2002-2003	CH	24	EOM	7
Gavliak (2006)	3(3)	LR: GOM	93%	82	2002-2005	G	19	STW	5
Hiadlovský and Kráľ (2006)	2(2)	LR	97%	856	2002-2005	G	18	STW	nd
Kráľ et al. (2007)	1(1)	FAA+DA	86%	190	2002-2004	G	36	FAA+STW	16
Boďa (2009)	1(4)	NN	94%	851	2002-2005	G	18	nd	18
Hurtošová (2009)	1(1)	LR	nd	427	2004-2006	G	85	MED, STW	4
Gurčík (2002)	1(1)	DA	nd	60	1998-2000	AG	35	EOM	5
Delina and Packová (2013)	1(4)	RA	21%	1,560	1993-2007	G	nd	COR	8
Harumová and Janisová (2014)	1(1)	LR	88%	53,206	2008-2011	G	20	STW	6
Boďa and Uradníček (2016)	1(4)	DA	71%	2,414	2009-2013	G	5	ALV	5
Gulka (2016)	1(1)	LR	79%	120,854	2012-2014	G	27	MISS, MCOL, STW	7
Mihalovič (2016)	2(2)	LR	69%	236	2013-2014	G	18	PT	5
Gavurová et al. (2017)	2(8)	CHAID	87%	1,182	2009-2014	G	102	STW	6
Horváthová and Mokrišová (2018)	1(1)	DEA	Nd	25	nd	TOU	12	ED	5
Kliestik et al. (2018)	1(4)	DA	83%	74,957	2012-2015	G	11	STW	6
Mihalovič (2018)	3(3)	GA	91%	1,280	2014-2017	G	58	STW	6
Valaskova et al. (2018)	1(1)	LR	Nd	62,533	2015	G	14	STW	9
Danišovská and Stachová (2019)	3(8)	REEM	82%	2,583	2009-2013	G	7	nd	nd
Gregova et al. (2020)	3(3)	NN	82%	64,757	2016-2018	G	14	STW	8
Horváthová and Mokrišová (2020)	2(2)	LR	95%	290	2016	NACE D	9	STW	5
Jenčová et al. (2020)	1(1)	LR	94%	856	2017	NFC, EEI	8	STW	5
Štefko et al. (2020)	2(2)	LR	87%	343	2016	HI	9	STW	7
Svabova et al. (2020)	2(3)	DA	94%	75,652	2016-2018	G	11	STW	nd
Horváthová et al. (2021)	2(2)	ANN	96%	444	2016	HI	11	none	11

Mazanec and Bartošová (2021)	1(1)	DA	91.50%	351	nd	NPO	14	STW	2
Štefko et al. (2021)	1(1)	DEA	Nd	343	2016	NACE D	17	nd	nd
Durica and Mazanec (2022)	3(3)	CART	88%	18,994		G	9	STW	nd
Gavurova et al. (2022)	2(2)	NN	100%	2,384	2018-2019	EEI	9	none	9
Mazanec et al. (2022)	1(1)	LR	97%	236	nd	NPO	14	STW	5
Svabova et al. (2022)	2(2)	DA	84%	88,252	2016	G	20	MCOL	6
Durica et al. (2023)	4(12)	BMLP	89%	75,649	2018-2019	G	25	MISS, MCOL	9
Horváthová et al. (2023)	1(1)	GTA	95%	186	2015-2021	C	5	DKA	5
Kanász et al. (2023)	6(18)	MTE	Nd	20,387	2013-2016	20 sectors	20	nd	nd
Mokrišová and Horváthová (2023)	2(2)	LASSO +LR + DEA	86%	1,349	nd	C	26	COR	7
Papík and Papíková (2023)	3(54)	LGBM	92%	106,407	2015-2019	G	46	none	46
Smorada et al. (2023)	1(1)	DA	72%	260	2013-2014	G	5	none	5
Valaskova et al. (2023)	1(5)	DA	89%	8,495	2020-2021	G	18	STW	7

Note: DKA - domain knowledge approach, EOM- test of equality of group means, MCOL – multicollinearity, MED median test, MISS - missing values, PT - pairwise testing.
Source: Chrastinová (1998), Zalai (2000), Hiadlovský and Kráľ (2005), Gavliak (2006), Hiadlovský and Kráľ (2006), Kráľ et al. (2007), Boďa (2009), Hurtošová (2009), Gurčík (2002), Delina and Packová (2013), Harumová and Janisová (2014), Boďa and Uradníček (2016), Gulka (2016), Mihalovič (2016), Gavurová et al. (2017), Horváthová and Mokrišová (2018), Kliestik et al. (2018), Mihalovič (2018), Valaskova et al. (2018), Danišovská and Stachová (2019), Gregova et al. (2020), Horváthová and Mokrišová (2020), Jenčová et al. (2020), Štefko et al. (2020), Svabova et al. (2020), Horváthová et al. (2021), Mazanec and Bartošová (2021), Štefko et al. (2021), Durica and Mazanec (2022), Gavurova et al. (2022), Mazanec et al. (2022), Svabova et al. (2022), Durica et al. (2023), Horváthová et al. (2023), Kanász et al. (2023), Mokrišová and Horváthová (2023), Papík and Papíková (2023), Smorada et al. (2023), Valaskova et al. (2023).

Each of these studies includes at least one novel predictive model for the financial difficulties faced by Slovak enterprises. The studies encompass journal articles, conference papers, and final theses, guaranteeing extensive coverage of scholarly viewpoints and practical insights. We included the papers in scientific journals and some final theses or conference papers, as they have contributed significantly to the development of bankruptcy prediction in Slovakia. The first study is the final thesis by Chrastinová (1998), and it is among the most frequently cited papers in this domain in Slovakia.

The models developed for Slovakia employed various methods, with notable shifts in techniques over time. Initially, traditional statistical methods like MDA and LR were predominant; however, in recent years, there has been a noticeable increase in the application of advanced machine learning methods, such as NN and DT. Currently, MDA and LR methods remain frequently used, comprising almost 60% of the models, while machine learning techniques are increasingly popular, constituting around 25% of the models. This evolution highlights the growing preference for techniques that can manage complex data structures with improved predictive accuracy. Research on Slovak bankruptcy prediction models has predominantly been published in Slovak and Central European journals, indicating regional interest and proficiency in this field. A number of articles have been published in journals with elevated worldwide rankings, signifying the selective distribution of Slovak research to a wider audience. A portion of these publications is published in Slovak, mostly from the start of bankruptcy prediction in Slovakia; nonetheless, the bulk is accessible in English, indicating a steady yet continuous transition towards international accessibility.

The number of variables in the studies varied from 5 to 102, while in the final models, from 2 to 46 variables were used. Most frequently, the final models contain 5 or 6 variables. More than 60% of studies created universal prediction models for all sectors of the national economy.

3.5 Analysis of Models in the V4

The body of literature on the development of bankruptcy prediction or financial distress models specifically for the V4 is limited, resulting in only 8 articles being included in Table 5.

The inaugural publication focused on the V4, was released in 2013 and specifically detailed the application of data envelopment analysis (DEA). Comparative analysis was conducted between the results and statistical models (MDA, LR).

Table 5. Bankruptcy prediction models constructed for the V4 economy.

Model	No. of methods	Best method	Accuracy	Sample size	Period	Sector	No. of ratios	Selection criteria	No. of ratios in model
Vavrina et al. (2013)	3(3)	DEA	V4: 86%	2,652 V4	1998-2012	AG	9	ED	8-9
Režňáková and Karas (2014)	1 (1)	BT	SK, 93% CZ, 89%, PL, 71% HU, 86%	2,652 V4	2007-2012	M	14	COR	5
Kliestik et al. (2018)	1(5)	DA	SK, 83% CZ, 85%, PL, 88% HU, 82%, V4, 86%	105,708 SK; 62,794 CZ; 28,908 PL; 252.371 HU	2015-2016	G	37	STW	9-13
Durica et al. (2019b)	1(1)	LR	V4: 88%	30,892 SK; 25,159 CZ; 9,293 PL; 98,202 HU	2015-2016	G	37	LRT, RSC	17
Pavlicko et al. (2021)	4(4)	Ensemble RobustBoost CART	SK, 92% CZ, 94%, PL, 95% HU, 95%, V4, 94%	55,124 SK; 97,479 CZ; 68,267 PL; 346,712 HU	2016-2018	G	27	STW	7
Pavlicko and Mazanec (2022)	1(1)	LR	SK, 92% CZ, 93%, PL, 95% HU, 95%, V4, 94%	2017: 667,582 (109,509 failed)	2016-2018	G	27	MIN	2
Tomczak (2023)	2(32)	LR	SK, 94% CZ, 99%, PL, 91% HU, 92%, V4, 91%	1,500	2009-2018	C	69	K-S, t test, W-L, STW	2-7
Valaskova et al. (2023)	1(5)	DA	SK, 89% CZ, 93%, PL, 96% HU, 91%, For V4: 90%	8,495 SK; 8,073 CZ; 432 PL; 3,693 HU; V4: 20,693	2020-2021	G	18	STW	6-14

Note: BT – Boosted Trees, LRT – Likelihood ratio test, MIN – minimal set of predictors, RSC – R Square characteristics. Source: Vavrina et al. (2013), Režňáková and Karas (2014), Kliestik et al., (2018), Durica et al. (2019b), Pavlicko et al. (2021), Pavlicko and Mazanec (2022), Tomczak (2023), Valaskova et al. (2023).

Primarily, models were developed using statistical techniques, as only one article did not report a statistical model (Pavlicko et al., 2021). SM accounted for 90% of the 51 models developed for the V4. This proportion of SM usage is unequivocally distinct from what is observed in Czechia, Hungary, Poland, and Slovakia. The stepwise approach is the predominant criterion for indicator selection, closely resembling the analysis of individual countries. Two articles provide models specifically designed for the V4, without including the local models for each country within the group. Conversely, 5 articles exclusively addressed several industries, representing 31% of the constructed models. Significantly, in contrast to the individual V4 countries, there is a scarcity of articles pertaining to the entire Group, and these articles are exclusively written in English. Notably, these publications are mostly local and do not include publications from major publishers like Elsevier, Springer, or Wiley.

3.6 Literature Review of the Accuracy of Models from the V4

So far, multiple researchers have validated previously published bankruptcy prediction models. The aim of studying these verifications is to statistically assess and compare the accuracy of the developed models in each respective V4 country. The aim is to identify the models that most precisely assessed the financial condition of companies based on subsequent empirical research. The outcomes of validation for models one year preceding the bankruptcy declaration of enterprises are displayed in Tables 6, 7, 8, 9, and 10. A minimum of 100 companies were incorporated in the scope for the chosen studies, and the verification results were published in a scientific journal. The V4-level models have not yet been independently verified; hence, a thorough literature assessment for the whole V4 cannot be presented.

3.7 Literature Review of the Accuracy of Models in Czechia

Table 6 displays five studies evaluating the efficacy of four models. The smallest research sample comprises 273 firms, and the largest exceeds 2,600. The effectiveness of the models varies from 50% to 98%.

Table 6. Literature review of accuracy of models in Czechia.

Model	Author's Accuracy	Čámská, (2016)	Kuběnka et al. (2018)	Kuběnka and Myšková (2019)	Karas and Režňáková (2016)	Kuběnka et al. (2024)	Mean of accuracy
Sample		430	273	1,501	2,659	961	
Research period		2012	2009-2013	2012-2013	1999-2013	2016-2019	
Neumaier and Neumaierová (2001)	74%	98%					98%
Neumaier and Neumaierová (2005)	95%	98%			50%		74%
Karas and Režňáková (2013)	94%		62%	57-68%			62.00%
Kliestik et al. (2018)	85%					83%	83%

Source: Čámská (2016), Kuběnka et al. (2018), Kuběnka and Myšková (2019), Karas and Režňáková (2016), Kuběnka et al. (2024).

Two models were evaluated in two distinct investigations. Their outcomes varied substantially. Despite the IN01 model achieving a 98% accurate classification rate for a single study, its high efficacy remains unverified.

3.8 Literature Review of the Accuracy of Models in Hungary

Hungary is distinct as an exceptional case among the V4 countries. It quickly became evident that internationally recognised and widely utilised models yielded much inferior outcomes when applied in Hungary, as compared to their original performance and the insights gained from other nations. Consequently, Hungarian researchers neglected to undertake the task of verifying or conducting backtests on bankruptcy models developed in foreign countries. Furthermore, Hungarian models have not yet been validated by independent academic researchers (Table 7).

Table 7. Validation methods applied to the Hungarian models.

Author	Accuracy of the best model in the article	Compare the performance to other method(s) applied on the same database	Compare the performance to other model(s) developed on a different database	Validate the performance on a separated testing subsample via partitioning	N-fold cross-validation	Robustness check
Hajdu and Virág (2001)	82%	x				
Virág and Kristóf (2005)	86%	x		x		
Virág and Kristóf (2006)	87%	x		x		
Kristóf (2008)	84%	x		x		
Virág and Kristóf (2009)	94%					x
Bozsik (2011)	84%	x		x		
Kristóf and Virág (2012)	94%	x		x		
Virág and Nyitrai (2013)	89%	x		x	x	
Bareith et al. (2014)	85%			x	x	
Ékes and Koloszár (2014)	73%	x	x	x		
Nyitrai (2014a)	78%			x	x	
Nyitrai (2014b)	76%			x	x	
Virág and Nyitrai (2014a)	89%	x		x		
Virág and Nyitrai (2014b)	83%	x			x	
Felföldi-Szűcs (2015)	70%			x		
Nyitrai (2015)	80%			x	x	
Inzelt et al. (2016)	86%				x	x
Nyitrai (2017)	90%				x	
Nyitrai and Virág (2017b)	81%			x	x	
Nyitrai and Virág (2017a)	91%			x	x	x
Kristóf (2018)	82	x		x		
Nyitrai (2018)	91%					x
Sütő (2018)	83%	x				
Nyitrai (2019a)	89%				x	x

Nyitrai (2019b)	83%	x		x	x	
Nyitrai and Virág (2019)	87%	x	x		x	x
Szenes and Dabi (2020)	80%					x
Horváth (2021)	78%				x	x
Ágoston (2022)	84%	x		x	x	
Márton et al. (2023)	78%			x		
Szántó (2023)	86%			x		

Source: based on the references from Table 2.

The Hungarian models exhibited classification accuracies ranging from 70% to 94%. When evaluating the classification power of various models, it is crucial to take into account the research objectives and databases. It is important to assess the differences in classification abilities of the models, taking into consideration the definition of the explanatory and target variables used.

In Hungary, the predominant approach for model validation entails dividing the database into a training subsample and a testing subsample. Subsequently, performance validation was carried out on the testing sub-sample, comprising 20 cases and representing 64.5% of the publications. Model performance was evaluated by comparing it to other classification methods applied to the same database in 15 cases (48.4% of the articles). Alternatively, it was examined using n-fold cross-validation, specifically with 15 examples, which accounted for 48.4% of the articles. The models underwent validation through a robustness check in 8 instances, which represented 25.8% of the publications. Model performance was evaluated against other models created by different methods using a separate database in two publications, which constituted 6.5% of the total articles. Out of the total publications, 22 articles (71.0%) utilised at least two validation techniques.

3.9 Literature Review of the Accuracy of Models in Poland

Table 8 displays the findings of a comprehensive literature review conducted on the accuracy of enterprise declarations one year prior to bankruptcy. The efficacy analysis exclusively focuses on SM due to its universal applicability.

Table 8. Literature review of accuracy of models in Poland.

Model	Author's Accuracy	Antonowicz (2010)	Juszczyk and Balina (2014)	Kisielińska (2016)	Tomczak and Radosiński (2017)	Tomczak (2018)	Iwanowicz (2018)	Mean of accuracy
Sampkle		208	180	110	10,700	1,353	139	-
Period		2003-2004	2009-2010	2009-2012	2000–2012	2007-2012	nd	-
Mączyńska (1994)	-				64%		90%	77.00%
Pogodzińska and Sojak (1995)	80%	61%	55%	60%				58.67%
Wierzba (2000)	92%	92%	65%		66%		92%	78.75%
Appenzeller (2001)	94%	89%						89.00%
Hołda (2001)	92.50%	86%	50%	80%	58%		92%	73.20%
Appenzeller and Szarzec (2004)	88%		59.20%		66%	78%		67.73%
Gruszczyński (2004)	91%			82.30%				82.30%
Hamrol et al. (2004)	96%	94%	75.80%	82.70%	56%	75%	93%	79.42%
Wędzki (2005c)	78%	87%						87.00%
Mączyńska and Zawadzki (2006)	97%	95%	75.80%	82.70%	69%	67%	92%	80.25%

Source: Antonowicz (2010), Juszczyk and Balina (2014), Kisielińska (2016), Tomczak and Radosiński (2017), Tomczak (2018), Iwanowicz (2018).

Only six verification studies satisfy the research sample requirement of 100 companies for SM, while 43 verification studies meet the criteria for ML and AI models. This table displays a compilation of six studies, each comprising ten models that have been previously presented in the table. Merely two models, Hamrol et al. (2004) and Mączyńska and Zawadzki (2006), were validated across all conducted studies. The observed results exhibited a notable decrease in effectiveness compared to the effectiveness reported by the authors of the models. The mean verification scores for the two items were 79% and 80%, respectively. This phenomenon is particularly evident in considerable sample sizes (Tomczak & Radosiński, 2017; Tomczak, 2018). This verification process revealed that these models might not be applicable to the manufacturing sector under consideration.

Evaluating the efficacy of ML and AI models poses significant challenges due to the absence of readily replicable and accurate data. An alternative approach to assess the efficacy of these models could involve utilising the identical database upon which researchers develop diverse ML and AI models. The online database containing the article Zięba et al. (2016) concerning Poland can be accessed at the following URL: https://archive.ics.uci.edu/dataset/365/polish+companies+bankruptcy+data. The publication occurred subsequent to the paper's printing, and numerous scholarly works employ it for research purposes. The dataset was also utilised in the Kaggle competition, accessible at the following URL: https://www.kaggle.com/c/companiesbankruptcy-forecast/data. The findings of the literature review pertaining to the utilisation of this database for constructing models are displayed in Table 9.

Table 9. Literature review of the Polish database.

Author	Accuracy of the best model in the article	Compare the performance to other method(s) applied on the same database	Compare the performance to other model(s) developed on a different database	Validate the performance on a separated testing subsample via partitioning	N-fold cross-validation	Robustness check
Paliński (2018)	97%	x		x		
García et al. (2019)	86%	x	x		x	
Pawełek (2019)	98%	x				
Wei et al. (2019)	97%	x	x	x		x
Wu et al. (2019)	97%	x		x		
Lahmiri et al. (2020)	95%	x	x		x	
Marso and El Merouani (2020)	92%	x		x		
Paliński (2020)	96%	x		x		
Uthayakumar et al. (2020)	98%	x	x		x	
Soui et al. (2020)	88%	x		x		
Smiti and Soui (2020)	96%	x		x		
Tsai (2020)	96%	x	x	x	x	
Zanka (2020)	81%	x		x		
Acharjya and Rathi (2021)	98%	x		x		
Aljawazneh et al. (2021)	99%	x	x	x	x	
Al-Milli et al. (2021)	96%	x			x	
Dzik-Walczak and Odziemczyk (2021)	91%	x		x	x	
Jin et al. (2021)	69%	x	x	x	x	x
Muslim and Dasril (2021)	97%	x		x	x	
Yang et al. (2021)	98%	x	x	x	x	x
Yotsawat et al. (2021)	99%	x	x	x	x	
Zelenkov and Volodarskiy (2021)	87%	x	x		x	x
Zhang et al. (2021)	98%	x	x	x	x	x
Aly et al. (2022)	97%	x	x	x		
Elhoseny et al. (2022b)	99%	x	x	x		
Elhoseny et al. (2022a)	95%	x	x	x	x	
Hilal et al. (2022)	99%	x		x		
Kumar et al. (2022)	99%	x		x		
Repetto (2022)	83%	x		x		
Safi et al. (2022)	89%	x	x	x	x	x
Saipriya et al. (2022)	95%	x		x	x	
Vaiyapuri et al. (2022)	99%	x	x	x		
Adisa et al. (2023)	97%	x		x		
Islam and Mustafa (2023)	95%	x	x	x	x	
Ranjbaran et al. (2023)	98%	x	x	x	x	
Qian et al. (2023)	95%	x	x	x	x	
Van der Schraelen et al. (2023)	91%	x	x	x	x	
Ainan et al. (2024)	98%	x	x	x	x	x
Amirshahi and Lahmiri, (2024)	99%	x		x	x	x
Yang et al. (2024)	95%	x	x	x	x	
Chakraborty and Ranjan (2024)	95%	x		x		x
Dervovic et al. (2024)	93%	x	x	x	x	x

Source: Paliński (2018), García et al. (2019), Pawełek (2019), Wei et al. (2019), Wu et al. (2019), Lahmiri et al. (2020), Marso and El Merouani (2020), Paliński (2020), Uthayakumar et al. (2020), Soui et al. (2020), Smiti and Soui (2020), Tsai (2020), Zanka (2020), Acharjya and Rathi (2021), Aljawazneh et al. (2021), Al-Milli et al. (2021), Dzik-Walczak, Odziemczyk (2021), Jin et al. (2021), Muslim and Dasril (2021), Yang et al. (2021), Yotsawat et al. (2021), Zelenkov and Volodarskiy (2021), Zhang et al. (2021), Aly et al. (2022), Elhoseny et al. (2022b), Elhoseny et al. (2022a), Hilal et al. (2022), Kumar et al. (2022), Repetto (2022), Safi et al. (2022), Saipriya et al. (2022), Vaiyapuri et al. (2022), Adisa et al. (2023), Islam and Mustafa (2023), Ranjbaran et al. (2023), Qian et al. (2023), Van der Schraelen et al. (2023), Ainan et al. (2024), Amirshahi and Lahmiri (2024), Yang et al. (2024), Chakraborty and Ranjan (2024), Dervovic et al. (2024).

Table 9 displays a total of 43 studies that utilised the aforementioned database. The predictive accuracy of the presented models falls within the range of 69% to 99%. The ensemble model, as proposed by Jin et al. (2021), achieved an accuracy rate of 69%. Furthermore, the models proposed by Aljawazneh et al. (2021), Yotsawat et al. (2021), Elhoseny et al. (2022b), and Amirshahi and Lahmiri (2024) demonstrated a classification accuracy of 99%. The mean efficacy of all studies is 94%, which closely approximates the target value of 96% obtained in the original studies. It is noteworthy to mention that a significant proportion of the works, approximately 55%, included the utilisation of diverse databases not only pertaining to Poland, as well as the development of models for these databases. The aforementioned databases encompassed various countries, including Australia, Finland, Japan, Germany, and Taiwan García et al. (2019). The models exhibited varying levels of accuracy.

3.10 Literature Review of the Accuracy of Models in Slovakia

Four studies conducted by Slovak authors concentrated on the validation of six previously developed Slovak models, utilising research samples that varied from tiny datasets of five firms to bigger samples of 27,029 and 3,329 enterprises (Table 10).

Table 10. Literature review of the accuracy of models in Slovakia.

Model	Author's Accuracy	Weissová (2017)	Weissova et al. (2016)	Kovacova et al. (2018)	Valaskova et al. (2020)	Mean of accuracy
Sampkle		5	5	27,029	3,329	
Research period		2011-2014	2014	2015	2016-2018	
Chrastinová (1998)	96%	40%	20%		87%	49%
Valaskova et al. (2018)	nd			94%		94%
Kliestik et al. (2018)	77%			29%	84%	56.00%
Kovacova and Kliestik (2017)	87%			90%		90%
Gurčík (2002)	nd				53%	53%

Source: Weissová, 2017; Weissova et al., 2016; Kovacova et al., 2018; Valaskova et al., 2020.

These validations evaluated models created throughout several timeframes, enabling a comparison between the models' predicted accuracy and actual results. The research, however, yielded inconclusive findings. For instance, whereas first models, like the inaugural Slovak model by Chrastinová (1998), had excellent accuracy (96%) as claimed by their developers, later validation tests indicated accuracy levels declining to 20-40% for some periods. Among the more recent models, the one by Valaskova et al. (2018) demonstrated higher validation accuracies, exceeding 93%.

3.11 Indicators Taken into Account in the Research and in the Models in Czechia

Figure 1 presents a succinct summary of the ratios evaluated in the research and models undertaken in Czechia.

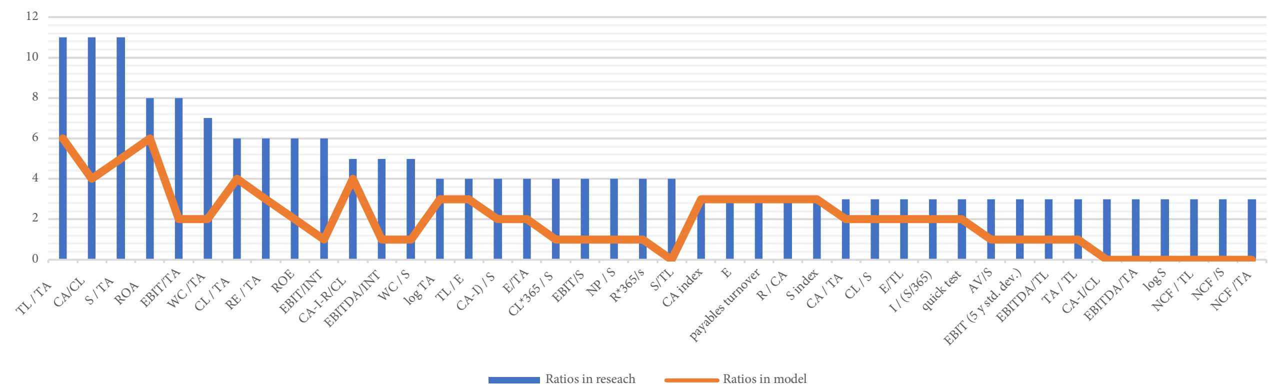

Figure 1. Indicators taken into account in the research in Czechia, 1990-2024.

Source: own calculations based on references from Table 1.

Note: AV- added value, CA – current assets, CL – current liabilities, E- equity, I- inventories, INT – interest, log – logarithm, NCF - net cash flow, NP – net profit, R- current receivables RE- retained earnings, S- net sales, TA – total assets, TL – total liabilities, WC – working capital.

It is important to note that not all studies provided the indicators utilised in the research, which may include Vochozka and Rowland (2015) and Vochozka et al. (2016). In the analysis of 21 studies, a total of 146 indicators were utilised, which were then reduced to 68 indicators incorporated in the models. In five studies, the indicators used a non-ratio format, predominantly reflecting size through the logarithm of total assets (Karas & Režňáková, 2013, 2017, 2018) and the 5-year standard deviation of EBIT as an indication of a multiperiod approach to variable definition (Karas & Režňáková, 2014). Additionally, Vochozka et al. (2015) implemented non-ratio indicators in the form of balance sheet components (such as equity, registered capital, or current liabilities) or profit and loss account elements (profit from ordinary operations).

The predominant category of financial ratios is solvency, including 32% of indicators, followed by profitability, which accounts for 22% of indicators. Solvency, profitability, liquidity, and activity metrics constitute 80% of the ratios analysed in models for Czech enterprises. The remaining 20% of ratios encompasses size variables, asset composition, debt structure, or cash flow configuration. The predominant solvency metric is the ratio of debt to total assets, which evaluates overall indebtedness; this has been utilised in eleven studies but only used in six models by various authors Dvořáček et al. (2012a), Dvořáček et al. (2012b), Valecký and Slivková (2012), Bemšet al. (2015), Němec and Pavlík (2016), Slavíček and Kuběnka (2016). Other frequently employed solvency ratios include debt to equity Jakubík & Teplý (2011), Karas & Režňáková (2014), Bemšet al. (2015) and current liabilities to total assets, which assess short-term indebtedness (Dvořáček et al., 2012a, 2012b; Karas & Režňáková, 2017, 2018). The predominant metric for assessing profitability is return on assets (ROA), which evaluates profitability from the standpoint of all stakeholders; this ratio was utilised in seven studies Neumaier and Neumaierová (2005); Valecký and Slivková (2012); Kalouda and Vaníček (2013); Slavíček and Kuběnka (2016); Karas and Režňáková (2018); Karas and Srbová (2019). In contrast, profitability from the shareholders' perspective (i.e., ROE) is seldom observed in models for Czech enterprises, as noted exclusively in Jakubík and Teplý (2011). The most commonly utilised metric for liquidity is the CR as referenced by Neumaier and Neumaierová (2005); Kalouda and Vaníček (2013); Bemšet al. (2015); Němec and Pavlík (2016). This contrasts with the prevailing tendency in bankruptcy prediction models, which favour Altman's working capital above total assets, as utilised in models for Czech enterprises in study of Vochozka et al. (2015) and Karas and Režňáková (2018). The primary focus of activity ratios is the overall evaluation of total asset usage, measured by the ratio of sales to total assets, known as total asset turnover Neumaier and Neumaierová (2005), Dvořáček et al. (2012a), Dvořáček et al. (2012b), Karas and Režňáková (2013), Machek et al. (2015). Particular emphasis was placed on inventory turnover (sales relative to inventory) or, more specifically, days sales in inventory.

3.12 Indicators Taken into Account in the Research and in the Models in Hungary

Despite extensive model development efforts, numerous significant relationships have been discovered in the decades-long history of bankruptcy prediction. However, there is still no consensus on which explanatory variables are most effective in predicting corporate failure in Hungary. The extensive variety of classification methods, combined with the diverse modelling databases from various environments, industries, and time periods, poses a significant challenge in formulating hypotheses about the causes of corporate failure and the mechanisms behind it.

In Hungary, there were 107 indicators that were considered as potential model variables in the 31 models that were referred to. The primary financial indicators used as input variables in bankruptcy modelling are based on well-established liquidity, profitability, indebtedness, leverage, turnover, cash flow, and size ratios commonly used in the field of corporate finance (Figure 2).

Furthermore, the relation of liquid assets to different balance sheet items, as well as the coverage of certain balance sheet or profit and loss items by net revenue, was also widespread in Hungary. Noncorporate financial ratios, such as macroeconomic indicators, market indexes, qualitative characteristics of companies, and loan repayment behaviour, were used less frequently. A total of 84 indicators were chosen as significant input variables in at least one distinct Hungarian bankruptcy model. The key financial ratios used in published models to predict corporate bankruptcy in Hungary include the CR, liquidity quick ratio (QR), proportion of liquid assets to current assets, cash flow to liabilities ratio, ROA, return on sales (ROS), equity ratio (ER), indebtedness ratio, working capital to total assets ratio, leverage ratio, total turnover ratio, inventory turnover ratio, and the natural logarithm of total assets and/or total sales.

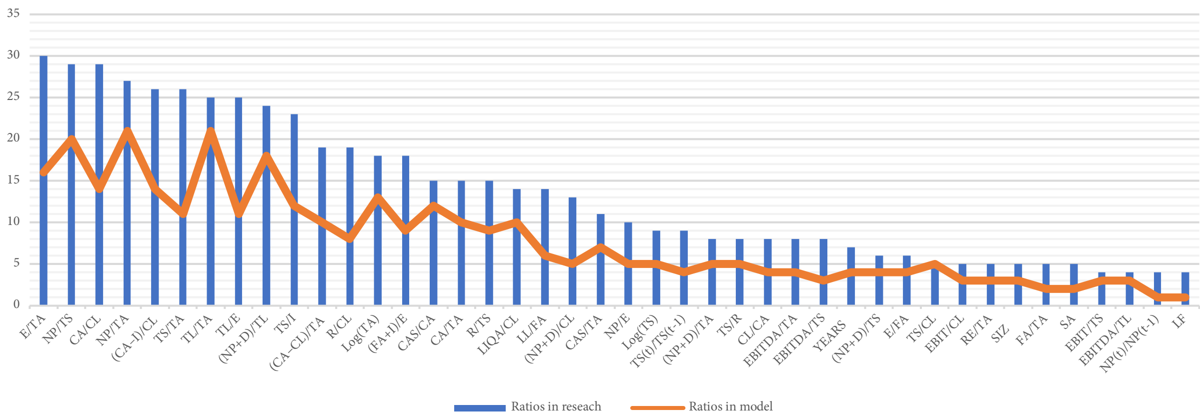

Figure 2. Indicators taken into account in the research in Hungary, 1990-2024.
Source: own calculations based on references from Table 2.
Note: D – depreciation and amortisation, FA – fixed assets, LF – Legal form, LL – Long-term liabilities, CAS – cash, SA – Sector of activity, SIZ – company size category, TS – total sales, YEARS – number of observed years in the database.

3.13 Indicators Taken into Account in the Research and in the Models in Poland

Figure 3 provides a concise overview of the ratios that were considered in the research and models conducted in Poland. A total of approximately 250 indicators were employed in the conducted studies, whereas the models ultimately yielded a reduction to 140 indicators, representing a decrease of over 100. The presented indicators can be classified into 10 different groups: liquidity (12 ratios), solvency (45 ratios), profitability (50 ratios), turnover (42 ratios), market position (24 ratios), dynamics (15 ratios), cash flow (13 ratios), sector indicators (25 ratios), company size (3 ratios) and others (12 ratios). The most substantial category comprises indicators related to profitability, while the least extensive category comprises indicators pertaining to enterprise size. It is important to acknowledge that certain studies did not achieve the precise determination of the indicator formula. In certain cases, the number of indicators initially considered was provided without including their respective formulas, while in other instances, only their names were provided.

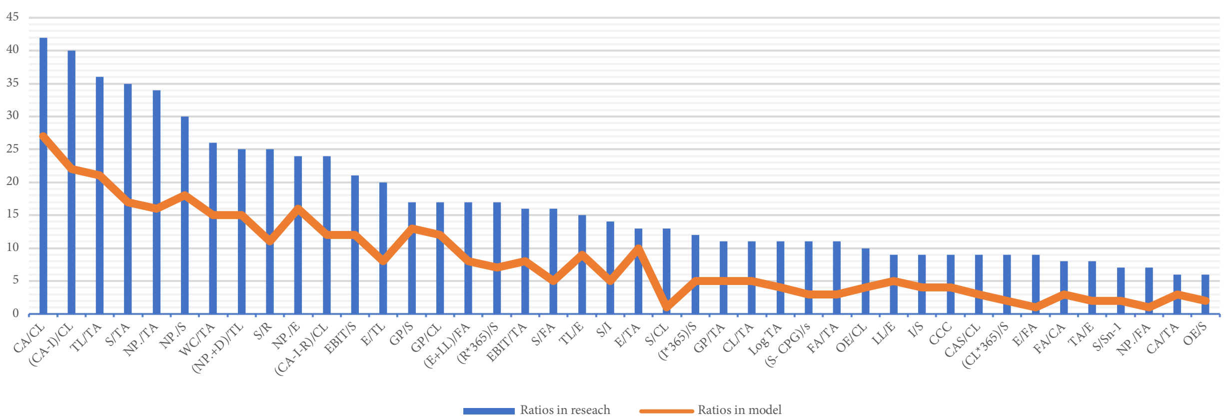

Figure 3. Indicators taken into account in the research in Poland, 1990-2024.
Source: own calculations based on references from Table 3.
Note: CCC - cash conversion cycle, CPG - cost of products, goods and materials sold, GP – gross profit, OE - operational expenses.

Upon examination of the frequency distribution of individual indicators within the studies, it is noteworthy that two liquidity indicators, namely CR and QR, exhibit a distinguished presence, appearing in more than 87% and 82% of the studies, respectively. Two additional liquidity indicators, namely the amount of working capital (in 53% of studies) and the cash ratio (in 49% of studies), are among the top 10 most commonly utilised indicators in research. In conjunction with liquidity ratios, there exist two indicators pertaining to leverage, namely debt and the coverage of total liabilities with the financial surplus ratio. Additionally, profitability indicators such as ROA and ROS are considered, alongside turnover indicators encompassing revenue and receivables turnover ratio. In contrast, the top 10 indicators commonly employed in models closely align with the top 10 indicators cited in research. The predominant liquidity indicators in the models are the CR and QR, although their frequency has decreased to 55% and 45% respectively. The process of selecting indicators resulted in a significant reduction in the frequency of occurrence for each individual indicator. It is noteworthy to mention that a significant proportion, specifically over 80%, of the indicators incorporated in the models exhibit a low frequency, with a maximum rate of 1%.

3.14 Indicators Taken into Account in the Research and in the Models in Slovakia

In the analysed Slovak studies, 156 distinct variables, primarily financial ratios, were employed. The TL/TA ratio was the most commonly utilised, serving as a possible predictor in 28 research (Figure 4), of which 20 (about 71%) identified it as a significant variable in the developed models. The second position is held by the ratio TL/E utilised in 26 studies, with 20 (63%) of them using this ratio as significant in the final model. The third most frequently used variable was EBIT/INT, included in 18 studies, although deemed significant in just 8 (almost 44% of the total). Of all the ratios, 64 were utilised just once.

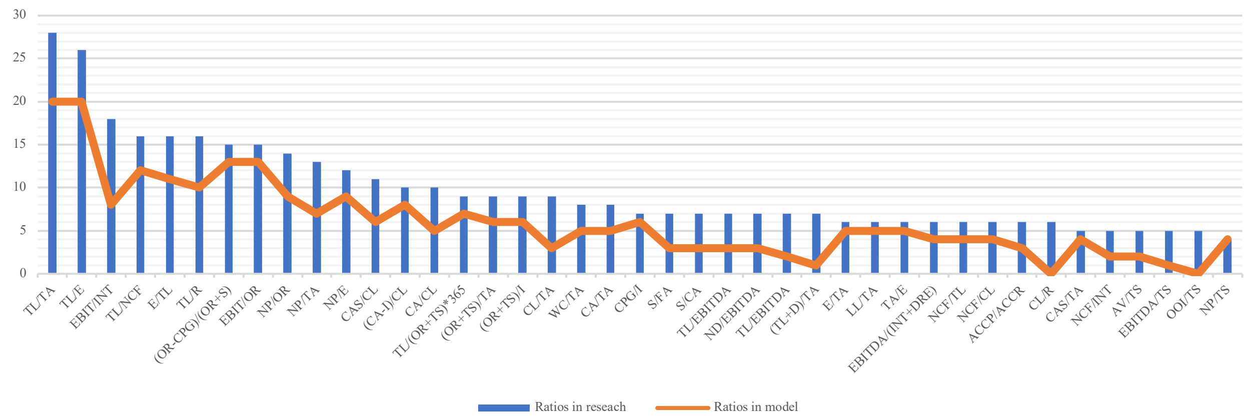

Figure 4. Indicators taken into account in the research in Slovakia, 1990-2024.

Source: own calculations based on references from Table 4.

Note: ACCP – accounts payable, ACCR – accounts receivable, DRE – deferred revenue, ND – net debt, OR – operating revenues, OOI other operating income.

3.15 Indicators Taken into Account in the Research and in the Models in the V4

When comparing the ratios examined in different countries, it is evident that there are fewer ratios relevant to the V4 (Figure 5).

This can be attributed to the limited number of publications specifically addressing the V4. The studies were conducted using a total of 91 indicators, out of which 61 were included in the models. The indicators were categorised into 8 out of the 10 previously discussed groups due to the absence of representatives for the market position and sector indicators group. The most extensive category comprises profitability and solvency indicators, each featuring 23 ratios. Conversely, the smallest category comprises company size indicators, each consisting of two ratios. An examination of all indicators revealed that only two are consistent across all studies: ROA and debt ratio (DR). However, only the DR was incorporated into the statistical models. Ratios such as CR, QR, ROA, ROS, current liabilities to total assets, and revenue turnover ratio are presented in six studies, accounting for 86% of the studies. However, these ratios are no longer included in models with such frequency. Consistently, studies and models tend to employ identical indicators. Furthermore, it is noteworthy to mention that the majority of the indicators in studies and models are present only once, namely 58% and 73%, respectively.

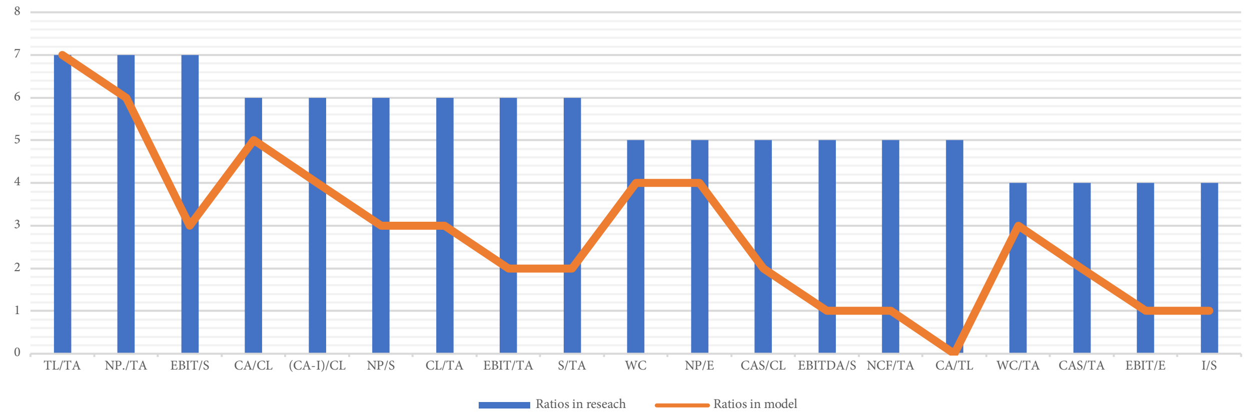

Figure 5. Indicators taken into account in the research in the V4, 1990-2024.
Source: own calculations based on references from Table 5.

3.16 The Most Frequently Used Methods to Construct Bankruptcy Prediction Models

Tables 11, 12, 13, 14, and 15 enumerate the methods employed in individual countries and across the V4. An examination of the tables reveals a progressive increase in the number of models developed over the years.

Table 11. The most frequently used methods to construct bankruptcy prediction models in Czechia with the year of publication.

Years—Methods	DA	LR	DT	NN	RF	XGB	SVM	GA	Others	Total
1990	0	0	0	0		0	0	0	0	0
2000	3	0	0	0	0	0	0	0	0	3
2010	19	16	5	19	1	0	1	0	6	67
2020	0	1	1	0	0	0	0	0	1	3
Total	22	17	6	19	1	0	1	0	7	73

Source: own calculations based on references from Table 1.

The early 1990s exhibited a scarcity of models, whereas the 2010s marked a substantial proliferation of models within individual countries and for the entire V4. It is unequivocally evident that discriminant analysis was the predominant method for model construction, with Hungary exemplifying the frequent application of logit analysis. Additionally, methodologies rooted in artificial intelligence and machine learning experienced significant prominence during the 2010s. A review of the summary data depicted in Figure 6 indicates that discriminant analysis and logit analyses were the most utilised methods, with neural networks occupying the third position. This part answers the first research question. There are many methods applied to predict the bankruptcy of companies within the V4, but mostly statistical methods are used.

Table 12. The most frequently used methods to construct bankruptcy prediction models in Hungary with the year of publication.

Years—Methods	DA	LR	DT	NN	RF	XGB	SVM	GA	Others	Total
1990	0	0	0	0	0	0	0	0	0	0
2000	5	7	2	5	0	0	0	0	0	19
2010	11	36	25	11	0	0	1	0	8	92
2020	0	5	0	1	1	0	2	0	1	10
Total	16	48	27	17	1	0	3	0	9	121

Source: own calculations based on references from Table 2.

Table 13. The most frequently used methods to construct bankruptcy prediction models in Poland with the year of publication.

Years—Methods	DA	LR	DT	NN	RF	XGB	SVM	GA	Others	Total
1990	5	0	0	0	0	0	0	0	0	5
2000	22	26	0	0	0	0	0	0	0	48
2010	35	38	16	36	15	1	31	8	68	248
2020	23	9	8	8	0	0	1	1	1	51
Total	85	73	24	44	15	1	32	9	69	352

Source: own calculations based on references from Table 3.

Table 14. The most frequently used methods to construct bankruptcy prediction models in Slovakia with the year of publication.

Years—Methods	DA	LR	DT	NN	RF	XGB	SVM	GA	Others	Total
1990	1	0	0	0	0	0	0	0	0	1
2000	6	3	0	4	0	0	0	0	1	14
2010	19	4	4	1	0	0	0	1	9	38
2020	11	9	12	6	1	18	3	0	47	107
Total	37	16	16	11	1	18	3	1	57	160

Source: own calculations based on references from Table 4.

Table 15. The most frequently used methods to construct bankruptcy prediction models for the whole V4.

Years—Methods	DA	LR	DT	NN	RF	XGB	SVM	GA	Others	Total
1990	0	0	0	0	0	0	0	0	0	0
2000	0	0	0	0	0	0	0	0	0	0
2010	6	2	1	0	0	0	0	0	1	10
2020	21	17	1	1	0	0	0	0	2	42
Total	27	19	2	1	0	0	0	0	3	52

Source: own calculations based on references from Table 5.

3.17 The Accuracy of Models Based on the Literature Review for the V4 countries

Table 16 presents an overview of the accuracy of models for individual countries in the V4. It is important to clarify that DA, LR, and NN denote the mean accuracy of all published models for a particular method as assessed by the model authors, whereas DA L signifies the mean accuracy of all models verified by independent researchers.

Table 16. The accuracy of bankruptcy prediction models for the most frequently used methods in V4.

Country |Method	DA	DA L	LR	NN	ML
Czech Republic	86%	79%	87%	95%	-
Hungary	86%	-	84%	84%	84%
Poland	90%	77%	85%	92%	94%
Slovakia	79%	68%	89%	92%	-

Source: own calculations based on references from Tables 1-10.

Consequently, ML denotes the mean accuracy of machine learning models utilising the public database for Poland and the mean accuracy of machine learning models for Hungary (Table 2). Upon analysing the table, it can be concluded that models employing machine learning techniques have the best accuracy. The highest accuracy of methods is achieved by light gradient boosting machine (LightGBM) as well as extreme gradient boosting (XGBoost) in the case of Poland, and neural networks in the case of Hungary. It is important to remember that discriminant analysis models validated by researchers exhibit lower accuracy than that claimed by their developers. Conversely, for models employing machine learning, either the same results or superior outcomes were achieved compared to those reported by the model developers. It is important to acknowledge that machine learning models cannot be replicated identically due to their black box nature, unlike statistical approaches. This statement answers the second and third research questions (Figure 6).

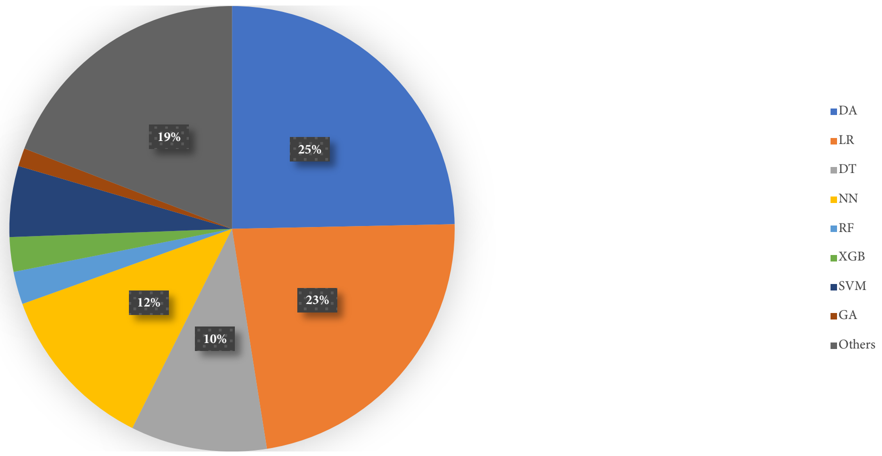

Figure 6. The most frequently used methods to construct bankruptcy prediction models in the V4, 1990-2024.
Source: own calculations based on references from Table 1-5.

The accuracy of the models was tested, but mainly for statistical models, except for Hungary, where independent researchers did not verify the existing models. The researchers demonstrate that statistical models are less accurate than their authors claim. Moreover, in the case of Poland, the accuracy was also tested for machine learning methods, because there are public databases. The results show that models employing machine learning techniques have the best accuracy.

3.18 The Most Frequently Used Indicators in Models and Research in the V4

Table 17 illustrates the most often utilised indicators in research and models for the whole V4. It is noteworthy that only a limited number of variables are consistently seen across individual countries.

Table 17. The most frequently used ratios in the V4.

Ratios	*Number of occurrences in studies*	*Number of occurrences in models*	*Percentage of occurrences in studies*	*Percentage of occurrences in models*
TL / TA	*107*	*75*	*73%*	*51%*
CA/CL	*98*	*55*	*67%*	*37%*
(CA-I)/CL	*82*	*48*	*56%*	*33%*
NP/TA	*81*	*50*	*55%*	*34%*
E/TA	*53*	*33*	*36%*	*22%*
NP/E	*51*	*34*	*35%*	*23%*

Source: own calculations based on references from Tables 1-5.

The dominant indicators in the V4 are two indicators from three groups: debt ratios (DR, ER), liquidity ratios (CR, QR) and profitability ratios (ROA, ROE). In comparisons across particular countries, it is futile to seek non-financial indicators (apart from the company size quantified by the logarithm of assets) or macroeconomic indicators, owing to their infrequent application in research and models. This pertains to the tendency of model developers to utilise prevalent indicators already employed in other models, particularly evident during the initial phases of model development, which drew inspiration from ”Western models”. Then, for the ratios specified in Table 17, nonparametric ANOVA was used to identify differences in the values between countries. Table 18 presents the results of nonparametric ANOVA in the period 2006-2021.

Table 18. Results of non-parametric ANOVA.

Year | Ratio	**Current ratio**	**Quick ratio**	**ROA**	**ROE**	**Debt ratio**	**Equity ratio**
2006	CZ-SK, CZ-HU, CZ-PL, HU-PL no	only SK-PL yes	all yes	all yes	CZ-HU, CZ-PL no	CZ-HU, CZ-PL no
2007	CZ-HU, CZ-PL no	CZ-HU, CZ-PL, SK-HU no	all yes	all yes	CZ-HU, CZ-PL, HU-PL no	CZ-HU, CZ-PL, HU-PL no
2008	CZ-PL no	SK-HU no	CZ-HU, CZ-PL no	CZ-HU no	CZ-HU, CZ-PL no	CZ-HU, CZ-PL no

2009	CZ-PL no	SK-HU no	CZ-PL no	CZ-SK, HU-PL	CZ-PL no	CZ-PL no
2010	all yes	all yes	only CZ-HU yes	CZ-SK, SK-HU, SK-PL no	all yes	all yes
2011	HU-PL no	SK-HU no	CZ-SK, SK-PL no	CZ-SK no, HU-PL no	SK-PL no	SK-PL no
2012	HU-PL no	all yes	CZ-PL, SK-PL no	CZ-SK no	all yes	all yes
2013	HU-PL no	all yes	CZ-PL no	CZ-SK no	all yes	all yes
2014	all yes	all yes	all yes	CZ-SK no	HU-PL no	all yes
2015	all yes	all yes	SK-PL no	CZ-SK, CZ-PL no	all yes	all yes
2016	all yes	HU-PL no	all yes	HU-PL no	all yes	all yes
2017	CZ-HU no	all yes	all yes	SK-HU no	all yes	all yes
2018	CZ-HU no	all yes	all yes	all yes	all yes	all yes
2019	CZ-HU no	all yes	CZ-PL	all yes	all yes	all yes
2020	CZ-HU no	all yes	all yes	CZ-SK no	all yes	all yes
2021	CZ-HU no	all yes	all yes	all yes	all yes	all yes

Source: own calculations.

Of the 6 indicators, the values of debt ratios (DR, ER) differ most frequently in the research period between countries, and these differences are statistically significant (all yes) with some exceptions at the beginning of the period (CZ-HU, CZ-PL, HU-PL no). For the remaining indicators, the differences are not so statistically significant because there are more inclusions, i.e. these differences are not significant among all V4 countries. In the absence of differences in indicator values between countries, there is a basis for building models for the entire V4. This part is an answer to the fifth research question.

3.19 The Number of Ratios Frequently Used in Models in the V4

Upon examining the different models within the V4 regarding the quantity of indicators incorporated, it is evident that this amount fluctuates between 3 and 8 variables, as seen in the summary in Figure 7.

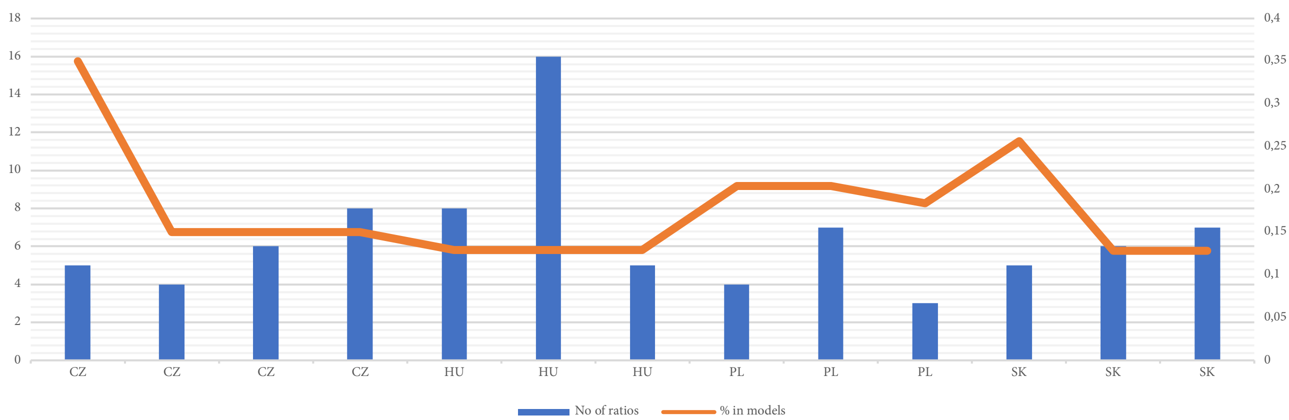

Figure 7. The number of ratios frequently used in models in the V4.
Source: own calculations based on references from Table 1-5.

Some models incorporate more factors; however, these models typically rely on machine learning techniques, as exemplified by Hungary. In this instance, five, eight, and sixteen indicators are present in the models, all corresponding to the identical frequency of occurrence, namely 13%. Conversely, for the other V4 countries, this figure does not surpass 7 indicators, but the frequency of occurrence varies. In the models, five variables are present in 35% of Czech works, 26% of Slovak works, and less than 18% of Polish works, therefore, failing to rank among the top three. Furthermore, the subsequent quantity of indicators ex aequo is 4 indicators and 7 indicators in Poland, which pertains to 20% of works, however, in Czechia, it accounts for 15% for the number 4 and 13% for the number 7. Another statistic present in the models is 3, representing 18% of the works related to the Polish economy. It is noteworthy that it occurs alone for this country, whereas it does not for the others. Furthermore, the primary approach for variable selection in each country is stepwise. This part answers the fourth research question. Models are usually constructed based on three to eight variables.

3.20 The Research Samples Used in the Studies Across the V4

The quantity of research samples varies considerably across different countries (Figure 8). The highest number of analysed works is in Poland; nonetheless, these works employed limited research samples. As the sample size increased, the proportion of works markedly diminished.

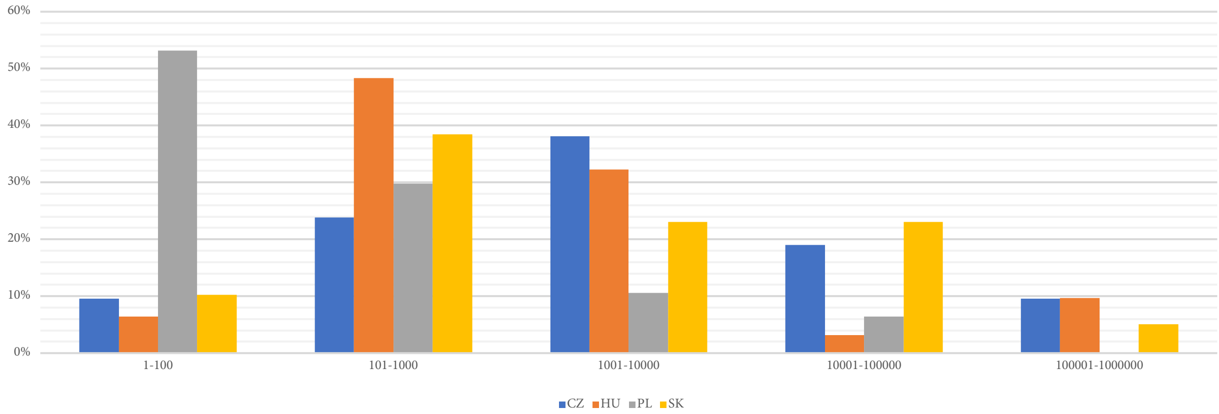

Figure 8. The research samples used in the models within the V4.
Source: own calculations based on references from Table 1-5.

For instance, 53% of the studies had research samples that did not surpass 100 firms, 30% had samples that did not exceed 1,000 enterprises, and 11% had samples that did not exceed 10,000 enterprises. Conversely, for 6%, the research sample did not surpass 100,000 firms. It is important to highlight that these figures are at the lower end of the spectrum, despite the fact that Poland has the highest number of operating enterprises within the V4. The greatest research samples are notably from Hungary, Czechia, and Slovakia, respectively. The largest sample for Hungary comprises 368,328 firms, for Czechia 241,380 enterprises, and for Slovakia 120,854 enterprises. In the largest sample size category of these countries, Hungary has three works, while Czechia and Slovakia each have two. It is worth adding that all the works using research samples exceeding 100,000 enterprises focused exclusively on statistical methods (MDA, LR), with the exception of one work from Slovakia. This section answers the seventh research question. Most of the research samples do not exceed 1,000 companies, except for Poland (most of the research samples are in the range of 1-100) and the Czech Republic (most of the research samples are in the range of 101-10,000).

3.21 The Number of Articles in Top Journals in which Research on Individual V4 Countries was Published

Numerous journals exist that publish research from the V4 countries. Nonetheless, several publications are of local significance, particularly when journals disseminate articles in the local language. Conversely, local journals publishing in English possess a broader scope, and in recent years, their numbers have increased, along with the volume of scholars publishing in English. It is worth noting that the majority of globally published research on bankruptcy prediction models, indexed in prestigious journals, is associated with the Elsevier publishing house (Dasilas & Rigani, 2024). In comparison to publications from the V4 countries, it is evident that only five papers were published by this publishing house, as seen in Figure 9.

Every country, except Hungary, has published one paper in Expert Systems with Applications. One study was published in Economic Modelling from Poland, and another in Socio-Economic Planning Sciences from Hungary. This part answers the last question. In most cases, the works are published in local journals with a few exceptions, such as Expert Systems with Applications.

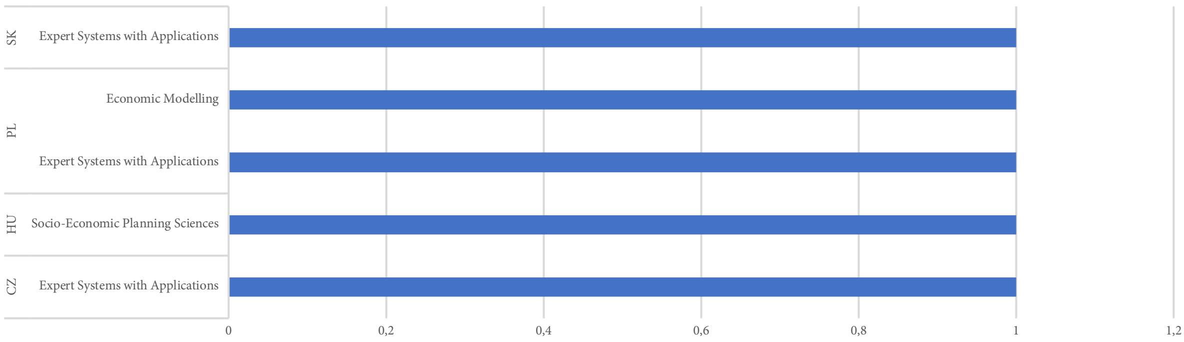

Figure 9. The top journals in which research on individual V4 countries was published.
Source: own calculations based on references from Table 1-5.

3.22 Upcoming Trends in Bankruptcy Prediction for the V4

The results suggest an increased adoption of artificial intelligence methodologies. There is a noticeable rise in the application of these approaches; yet, their prevalence remains limited. This growth is expected to transpire, particularly when considering the dissemination of databases in public repositories from the relevant countries addressed in this article. The sharing of data will enhance researchers' interest in the V4 analysis; for instance, the database for Polish enterprises is often utilised (Fig. 7). The majority of models were developed primarily using financial indicators, with a minor inclusion of non-financial indicators and no use of text analysis to assess the utility of off-balance sheet information on the firm. Off-balance sheet information may encompass news articles and social media posts. To date, no similar endeavour has been undertaken in the V4 countries. Furthermore, an increasing number of studies have to be published in esteemed journals to enhance interest in the analysis of the V4 countries and other Central and Eastern European nations.

4. Discussion

The research comprehensively examines the research focused on developing bankruptcy prediction models for specific countries and the whole V4. The investigations revealed that the predominant methods employed were discriminant analysis and logit analysis, with neural networks ranking third. In comparison to general global reviews, the findings are analogous (Bellovary et al., 2007), with the distinction being the reduced application of neural networks and machine learning techniques in the V4. It seems distinct in comparison to Alaka et al. (2018), where the increased utilisation of machine learning techniques is evidently apparent. The application of machine learning techniques is far less prevalent than in developed economies (Ahmed et al., 2022). Furthermore, when juxtaposing the results with those aggregated for the V4, the proportion of statistical models in the research is much less in contrast to Kovacova et al. (2019). It is noteworthy that the study of Kovacova et al. (2019) examined 103 models, whereas our article studied 147 models. The analysis predominantly focused on the Polish studies, as 61% of them originated from Poland. We have included a higher number of studies from Hungary (five times more) and Slovakia (three and a half times more), which also impacted the outcome. The amounts of contributions from individual countries in our work are more comparable; hence, the values utilised in one country do not substantially influence the outcome, unlike in Kovacova et al. (2019). An investigation of the evaluation of the Hungarian article Kristóf and Virág (2020), reveals a significant prevalence of logit analysis and neural networks. This substantially affects the outcome of the comparison of the approaches employed in the review.

It is noteworthy that, to date, no efforts have been undertaken in Hungary to publish the validation of any previously constructed models by independent academic researchers. Among the V4 nations, this is the sole country where no model validation corroborated the efficacy of models presented by their developers. Models based on machine learning have the best accuracy, which is unsurprising. Furthermore, for Poland, further verification was conducted due to its status as a publicly accessible resource, frequently utilised for developing models employing artificial intelligence and machine learning techniques. The efficacy achieved by other authors averages 94% over 43 publications, which is a commendable outcome. Furthermore, the accuracy of discriminant analysis models is much inferior to the figures reported by their authors, ranging from 68% to 79%. The average accuracy values for discriminant analysis are comparable to those in Alaka et al. (2018), but the results for neural networks and logistic regression are superior. The authored works have often been published by local publication outlets, and over time, they have started to be published in English. Only a limited number of journal articles were published by top publishing houses.

The number of indicators incorporated in the models across the V4 fluctuates between 3 and 8. In the models, five indicators are present in 35% of Czech works, 26% of Slovak works, and less than 18% in Poland and Hungary. In comparison to Kovacova et al. (2019), five indicators rank second. The leading position is occupied by employing four variables, which have a utilisation rate of 29%. Furthermore, the primary approach for selecting indicators for models in each of the examined countries is stepwise. This is the preferred approach for constructing statistical models (Alaka et al., 2018), and the majority were developed using these approaches in the V4. The majority of the studies utilise research samples of up to 1,000 firms, consistent with the studies conducted in other countries (Kumar & Ravi, 2007; Alaka et al., 2018; Dasilas & Rigani, 2024). The smallest samples are created for Poland, barely surpassing 30,000, whilst the largest samples are for Hungary, far over 100,000.

It is worth pointing out that the obtained results are different from those presented by Tomczak (2021). In those studies, there are no mean differences between the values of ratios in the groups for debt indicators (DR, ER). The work compared differences between only sectors and not countries for stock companies.

In comparing the results to prior review studies, it is important to note that not all give a model analysis; some only identify the authors for each country (Kral et al., 2018; Prusak, 2018), while others concentrate on various features, such as the results of bibliometric analysis (Prusak & Karas, 2024; Ahmed et al., 2022). However, these studies possess several limitations. They exclusively encompass publications related to Poland and Hungary, thus diminishing the quantity of studied works. Simultaneously, this limitation mitigates the influence of numerous works in the comparative analysis for the whole V4. Although the study offers a comprehensive insight into bankruptcy prediction models for the V4 countries, its findings may be generalised to regions or countries with differing economic conditions only after careful consideration. However, we consider the study valuable also for international readers who want to understand better the development and application of prediction models in emerging market conditions. Another possible weakness of the study is that the models reviewed are drawn from multiple sectors, and the reviewed models were created using various methodologies and data sources. This heterogeneity could affect the generalizability of the conclusions. Nevertheless, by examining a wide range of models, the study highlights universal predictors and methodological trends, which can be valuable for future research and the prediction of the companies' financial state development. A different limitation of the work is the lack of precise specification of all indicators taken into account in the research in some works, and the assumption that only the name of the indicator is given, without its formula. This is due to the fact that in some works it is not specified which indicators were taken into account in the research, only it is written, e.g. the number of indicators taken into account in the research is 100. On the other hand, in some works only the names of the indicators are given, e.g. ROA, ROE, without specifying whether the numerator should be gross, net profit or maybe EBIT.

Conclusions

The article examines several corporate bankruptcy prediction models developed for specific countries and the whole V4 from Q1 1990 to Q1 2024. The review encompasses an evaluation of the works, considering the chronology of their creation, the sample size, the diversity of methodologies and best methods employed in various studies, classification accuracy, research period, the number of indicators in the studies and models, the sector analysed, and the variable selection techniques utilised for model development. The review considers 21 papers for Czechia, 31 for Hungary, 49 for Poland, 39 for Slovakia, and 7 for the entire V4. Furthermore, 43 papers pertaining to Poland were examined to assess the accuracy of machine learning methodologies used to study samples sourced from open databases of a particular nation. To a certain extent, the accuracy of statistical models was validated by an analysis of model correctness performed by independent researchers. The accuracy of enterprise classification by statistical models is considerably inferior to that exhibited in the authors' research. Conversely, models utilising machine learning exhibit superior accuracy via independent validation. Notwithstanding this, the predominant techniques employed within the V4 are statistical ones.

The quantity of research samples varies considerably across different countries and the majority of the studies utilise research samples of up to 1,000 firms. It should be pointed out that all the works using research samples exceeding 100,000 enterprises focused exclusively on statistical methods (MDA, LR) except one work from Slovakia and did not consider machine learning-based methods.

The article delineates the indicators considered in the research and those employed to develop the models. The research considered a varying number of indicators for each country: Czechia had 146, Hungary 107, Poland 250, Slovakia 156, and for the V4-level research, it was 91. Nevertheless, only a limited number of variables are consistently observed across countries with comparable frequency. The predominant ratios in the V4 are the total debt ratio, equity ratio, the current liquidity ratio, quick ratio, return on equity and the return on assets. But the differences in values between countries are statistically significant for debt indicators, but not so much for the others. In the absence of differences in indicator values between countries, there is a basis for building models for the entire V4.

In examining other commonalities among nations, it is important to note that non-financial or macroeconomic variables are often absent from the most often utilised metrics, owing to their infrequent application in research and models. This pertains to the observation that, in several instances, model developers employ a shared array of variables already utilised in other models.

In conclusion, the models have predominantly been constructed using financial indicators; however, there has been no effort to employ text analysis to determine the utility of off-balance sheet information on companies operating in the V4. Off-balance sheet information might encompass news articles and social media posts. This might be an emerging trend in the development of financial distress models in the V4. The research findings ought to be disseminated in prestigious journals, as there have been limited publications on the V4 in leading journals to date.

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