12th International Scientific Conference

BUSINESS AND MANAGEMENT 2022

May 12–13, 2022, Vilnius, Lithuania

ISSN 2029-4441 / eISSN 2029-929X
ISBN 978-609-476-288-8 / eISBN 978-609-476-289-5
Article Number: bm.2022.850
https://doi.org/10.3846/bm.2022.850

NEW PERSPECTIVES ON MANAGEMENT AND RESILIENCE OF BUSINESS ORGANISATIONS *http://vilniustech.lt/bm*

MODELING THE FINANCIAL DISTRESS OF SLOVAK COMPANIES USING VARIOUS DECISION TREES

Marek DURICA*, Jaroslav MAZANEC

Department of Quantitative Methods and Economic Informatics,
Faculty of Operation and Economics of Transport and Communications, University of Zilina,
Univerzitna 8215/1, 010 26 Zilina, Slovak Republic

Received 05 March 2022; accepted 21 March 2022

Abstract. Financial health prediction is the key topic for many entities in building reliable partnerships with other subjects. The paper aims to predict the financial distress of Slovak companies from various industries using specific models based on decision trees such as CART, CHAID, and C5.0. These algorithms are the most used tools for identifying key variables explaining financial health and providing a prompt and understandable implementation in risk management. These models are based on a final set of almost 19,000 companies and a wide range of financial ratios from the Amadeus database. Finally, the results of the individual and ensemble decision trees were compared to identify the best model for the prediction of the financial distress of Slovak companies. The results demonstrate that C5.0 best classifies entities into financial-distressed and non-financial-distressed companies.

Keywords: company financial distress, financial ratios, decision tree, prediction model, classification ability.

JEL Classification: C38, G33.

Introduction

Risk management is a crucial part of corporate governance. Its task is to draw attention to potential financial problems or even bankruptcy well in advance using relevant tools. For the global economic crisis in 2008–2009 and the consequences of the COVID-19 pandemic, the importance of prediction models has increased.

The article aims to propose a prediction model as a tool for early warning of the potential threat of bankruptcy for all Slovak companies, regardless of economic segment. This tool can be a universal tool for all Slovak companies. The key motive is to provide a simple and efficient tool for everyday use from the perspective of many stakeholders. In other words, the added value lies in simply identifying potential financial problems. Our research includes a detailed analysis of financial indicators as input variables in identifying relevant indicators estimating the financial distress of Slovak companies. This demanding multi-step process leads to relevant prediction models based on the resulting performance metrics. Our research contributes to filling the gap in estimating the financial distress of Slovak companies from various industries using decision algorithms. We see the benefits in universal models for all sectors with quick feedback for the assessed company. However, these models are important also for current and potential foreign investors in choosing a reliable business partner because the Slovak Republic is one of the countries with investment potential for its location in Central Europe, but especially membership in the EU, Eurozone, and Schengen. Foreign investors, especially from neighbouring countries and other European countries, play a significant role in the national economy.

Using CART, CHAID, and C5.0 algorithms, individual and ensemble classification decision trees are created. These models are designed to predict financial problems a year in advance and are created using a precisely prepared database of real Slovak companies. The models work with nine financial ratios and size and SK NACE category identifiers.

We decided to use algorithms that generate decision trees. Many studies show that these tools are appropriate and model financial stress and their prediction. In addition, according to Jabeur and Fahmi (2018) and other authors, decision trees achieve better predictive power than traditional multidimensional discriminant analysis

* Corresponding author. E-mail: *marek.durica@fpedas.uniza.sk*

or logistic regression. On the other hand, in terms of predictive power, decision trees are comparable to artificial neural networks and other data mining tools. All these tools are suitable for model even very complex relationships between variables, even using incomplete, noisy, or otherwise poor-quality data. The decision trees themselves are very illustrative and relatively easy to interpret and implement in practice.

The paper is divided into the following parts. First, the literature review describes current theoretical and empirical knowledge about estimating financial distress using decision trees. The methodology explains an approach to creating decision trees using several species, such as CART, CHAID, and C5.0. These models are compared based on selected performance metrics and the classification of companies as financial-distressed and non-financial-distressed. We emphasise the selection of relevant indicators as a basic pillar in designing models based on decision tree algorithms. In the discussion, we compare our results with previous research and outline a future vision in a timely estimation of the company's financial distress. Finally, we summarise the key findings of the research.

1. Literature review

Decision trees are one of the key tools for easily classifying companies as financial-distressed and non-financial-distressed based on financial indicators explaining the (in)effective business management approach. Unfortunately, many studies focus on complicated methods without applicability in day-to-day practice for directors, investors, and managers in identifying potential threats to prevent economic damage.

Korol (2019) explained that financial forecasting is one of the key topics of financial management. Csikosova et al. (2019) are aware that existing models need to be modified for specific conditions in different industries based on previous research. Their research is based on multicriteria analysis such as the Altman, Taffler, Springate model, and IN index. Chen (2016) identified fraudulent financial statements using a hybrid data mining approach. However, significant indicators were chosen using the classification and regression tree (CART) and the Chi-squared interaction detector (CHAID). The CHAID-CART model achieved the best overall accuracy of almost 88%. Nyitrai and Virág (2019) founded that CHAID is an effective way to handle outliers of financial ratios to model performance.

On the other hand, Chen (2012) emphasised that a support vector machine is a more appropriate method than traditional techniques or decision trees based on comparing statistical methods, decision trees, and neural networks. Jabeur and Fahmi (2018) demonstrated that performance metrics decision trees as a traditional method are better than discriminant analysis or logistic regression. Likewise, Li et al. (2010) compared a prediction model based on CART with frequently used classical statistical methods and other mining methods. Chandra et al. (2009) applied several hybrid techniques such as multilayer perceptrons, random forest, logistic regression, support vector machine, classification, regression trees, ensembling, and boosting to increase the prediction accuracy proposed model for dotcom enterprises. Delen et al. (2013) identified financial indicators affecting business performance using various decision tree algorithms similar to previous research (Chen, 2012). Decision tree algorithms such as CHAID and C5.0 were the best ways to increase model accuracy. In addition, earnings before tax to equity ratio and net profit margin were the most important indicators using sensitivity analysis.

Zięba et al. (2016) proposed a new approach to estimating financial distress using extreme grading boosting for learning an ensemble of decision trees for Polish companies based on data from the Emerging Markets Information Service (EMIS) from 2007 to 2013. Durica et al. (2019) suggested a prediction model for Polish companies using decision trees based on relevant data from the Amadeus database. This model achieves more than 98% predictive power. In addition, more than 83% of Polish companies in financial distress are correctly classified using the proposed model. Berent et al. (2017) presented a new methodological approach to creating a prediction model for Polish companies using a double stochastic Poisson process with a multi-period prediction horizon. Wieprow and Gawlik (2021) dealt with the potential bankruptcy risk of tourist companies listed on the Warsaw Stock Exchange.

On the other hand, Andreica (2012) analysed data on 132 Romanian companies (66 failed companies) from 2008 to 2010 to create a prediction model as an early warning system to prevent financial distress using the CHAID decision tree. Popescu and Paun (2016) applied macroeconomic indicators such as economic growth, labour productivity, employment, and average net earnings, unlike previous research, to predict European companies' financial distress. Popescu et al. (2017) proposed a prediction model as a warning system against potential problems in financial stability. One of the key methods is decision trees and neural networks. Moreover, the predictive power was enhanced by principal component analysis. The total sample consists of 346 Romanian companies (173 failed companies). The results showed that the best indicator dividing the sample into healthy and unhealthy companies is cash flow to operating revenue.

On the other hand, the neural network determines significant variables such as cash flow to operating revenue, profit margin, return on equity, operating revenue per employee, liquidity ratio, and shareholders' funds per employee. However, the most significant variable in both models was cash flow to operating revenue. Popescu and Dragotă (2018) built on previous research on financial distress in Romania. This research was extended to estimate financial distress in other countries such as Bulgaria, Croatia, the Czech Republic, and Hungary.

Popescu and Dragotă (2018) reapplied the CHAID and network neurons. The total sample consists of less than 20,000 companies. They used 24 financial indicators out of a total of 32 are used. Other indicators were removed for multicollinearity and missing values. These indicators were broken down into two main approaches: the stock and flow approach. Finally, the best variables for all post-communist countries were summarised to estimate the company's financial distress. Popescu and Dragotă (2018) recommended for Czech, Hungarian and Romanian companies the application of flow-approach variables using CHAID models in contrast to other countries. Manogna and Mishra (2021) identified relevant input variables for creating a prediction model using sensitivity analysis. These data on more than 1900 Indian companies were inputs in models based on decision tree algorithms such as CHAID, CART, C5.0, and quick unbiased statistical tree (QUEST). The results demonstrated that C5.0 and CHAID decision trees were the best algorithms providing excellent model metrics. The key indicators included the net profit margin and the total assets turnover rate as appropriate financial indicators determining the performance of Indian manufacturing companies.

Jayasekera (2018) explained that QUEST is a suitable method for estimating financial distress. Jan (2018) developed an effective tool for estimating financial fraud for financial markets using an artificial neural network (ANN), a support vector machine (SVM). These approaches identified significant variables for detecting financial fraud using four different decision trees CART, CHAID, C5.0, and QUEST. Significant indicators included audited by BIG4, the restatement of financial statements, quick ratio, return on assets, pre-tax profit ratio, debt ratio, operating income to sales revenue, current ratio, and type of audit report. On the other hand, SVM identified only three significant indicators, namely operating expense to sales revenue, audited by BIG4, and inventory to current assets. Only two of these indicators are significant in both selections. These financial and non-financial indicators were applied to modeling using selected tree models. The results show that ANN-CART has the best results in the classification with an accuracy of more than 90% in identifying fraud with financial statements. Ashoori and Mohammadi (2011) estimated the bankruptcy of Iranian companies using CART and the multilayer perceptron (MLP). The results show that the accuracy of the MLP-CART model is approximately 84.88–86.96% in the training and test sample.

2. Methodology

Creating a prediction model can be divided into two basic phases. The first phase is data collection and preparation. In this phase, potential predictors are also identified, multicollinearity is analysed, and a final data set suitable for the second phase implementation is created. The second phase is the creation of the models themselves and the quantification of their predictive ability.

2.1. The data preparation

We have identified the possibility of using algorithms generating decision trees to create models for predicting financial health in the Slovak economy due to the dynamic development of the current economic environment and ex-ante financial instruments. As part of the study of the scientific literature, we identified 25 financial ratios widely used in this area. We have supplemented these potential predictors with a company size identifier and an SK NACE identifier. The data was obtained from Amadeus.

To create the models, we chose the most up-to-date data, calculated from companies' financial statements for 2018 and 2019. In the first step, we verified the data consistency, and many companies were excluded from the initial sample of more than 660 thousand companies. Subsequently, we identified and excluded outliers based on the interquartile range.

The target (output) variable that will be modelled is the *company financial distress* expressing the company's financial status in 2019. The company has the status of a non-financial-distressed company according to currently valid legislation of the Slovak Republic. A company in crisis is an entity in bankruptcy or is in danger of bankruptcy.

Exactly 9,497 companies (12.6%) of the original sample had the status of a non-financial-distressed company in 2019. Therefore, 9,497 companies were randomly selected from 66,152 financial-distressed companies to eliminate a large sample imbalance. The representativeness of this sample was verified and confirmed by statistical tests.

It was necessary to analyse multicollinearity because several financial indicators (ratios) are closely related. Therefore, we analysed these variables' correlation matrix and variance inflation factors (VIFs) and identified undesirably high degrees of multicollinearity for many variables. By eliminating the individual variables step-to-step, we reduce the degree of multicollinearity to an acceptable level (VIF is less than five). In this way, we obtain the final set of nine financial indicators, including indicators from all four basic areas of the company's financial health analysis. Table 1 presents these potential predictors and their VIF values. In addition, the discriminant ability of these variables was verified by relevant statistical tests.

Table 1. The final list of financial ratios

Ratio	Ratio type	VIF
Asset Turnover Ratio (SAL/TA)	Efficiency (Activity)	1.614
Current Ratio (CA/CL)	Liquidity	1.741
Return on Equity (ROE)	Rentability	1.014
Return on Assets (ROA)	Rentability	2.484
Debt Ratio (TL/TA)	Leverage	1.840

End of Table 1

Ratio	Ratio type	VIF
Cash and Cash Equivalents to Total Assets (CASH/TA)	Liquidity	1.239
Return on Sales (ROS)	Rentability	2.323
Non-current Liabilities to Total Assets (NCL/TA)	Leverage	1.025
Liability Turnover Time (TL/SAL)	Efficiency (Activity)	1.776

Finally, we divided the sample into training (approximately 80% of companies) and test (approximately 20% of companies) sub-samples. The training sample was used in the model learning phase. The five-fold cross-validation technique was also applied to the model selection itself. The test sample was used only to evaluate the resulting models in quantifying the predictive ability.

2.2. The modelling

This part focuses on selecting and applying suitable data-mining tools to the prepared data set. We decided to use algorithms that generate decision trees.

Decision trees provide relatively simple classification rules based on comparing a variable value with a constant (division criterion). Furthermore, they are widely used to create prediction models for easy interpretation. These algorithms can deal with inconsistent data and describe nonlinear relationships between variables.

The decision tree is usually represented in a dendrogram representing the divisions of a relatively large heterogeneous dataset into smaller, more homogeneous subsets.

The generation of the tree itself begins with the initial dataset (so-called root node), which is divided into sub-nodes. The nodes created in this way are repeatedly divided into more homogeneous nodes. The nodes can always be divided into two sub-nodes (binary tree) or even more sub-nodes (non-binary tree). The division itself in the individual nodes continues until the termination criterion is reached. This criterion usually consists of several specific conditions. This approach generates the so-called maximum tree that flawlessly explains relationships in the training set. However, this tree is often over-estimated and has a problem with generalisation. Therefore, we apply k-fold cross-validation and pruning techniques.

The homogeneity or purity of the nodes is quantified based on the measure of impurity. The most used measures are entropy, information gain, Gini index, and the p-value of the χ^2-test.

We use CART, CHAID, and C5.0 algorithms for modelling. These algorithms are most used in the field of predictive modelling of the financial health of companies.

The CART algorithm generates a binary decision tree and employs the Gini index as a measure of impurity. At first, the algorithm creates a maximum tree, which is post-pruned to avoid the problem of overtraining the model. The stopping criterion for generating a tree is a combination of several conditions. There are a maximum of five levels of node division, and a node is not divided if it contains a maximum of 100 companies or its division leads to some sub-node with less than 50 companies.

The CHAID algorithm generates non-binary decision trees and the p-value (with a significance level of 0.05) of Pearson's χ^2-independence test is employed as a criterion for node division. During the creation of the model, the criterion of a maximum of three levels of node division and a minimum number of 100 companies per node and 50 companies per sub-node was set.

Algorithm C5.0 represents an algorithm that employs entropy as a measure of impurity in the nodes. The algorithm creates a binary decision tree with clean leaves (all companies in the leaves belong to a group of financial-distressed or non-financial-distressed companies). This algorithm is characterised by the fact that excess node division is eliminated in generating the tree.

For CART and CHAID algorithms, individual classifiers are generated and ensemble classifiers using the bagging and boosting technique. In this case, a five-fold cross-validation technique was used within the training sample to find the optimal model.

2.3. The models testing

In this phase, we used the classification table, the model quality measures derived from it, and the size of the area under the ROC curve to evaluate and compare the created models. The classification table summarises the number of correctly and incorrectly classified positive and negative cases. These indicators are the numbers of true negative (TN), false positive (FP), false negative (FN), and true positive (TP) cases. In our case, non-financial-distressed companies are positive, and financial-distressed companies are negative. We evaluate created models using several derived characteristics:

– Overall Accuracy $ACC = \dfrac{TP+TN}{TN+FN+FP+TP}$;

– True Positive Rate (sensitivity) $TPR = \dfrac{TP}{TP+FN}$;

– True Negative Rate (specificity) $TNR = \dfrac{TN}{TN+FP}$;

– Precise $PR = \dfrac{TP}{TP+FN}$;

– F1-score $F1 = 2 \times \left(\dfrac{PR \times TPR}{PR + TPR} \right)$;

– Mathews Correlation Coefficient

$$MCC = \frac{TP \times TN + FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}};$$

– The area under the ROC curve AUC.

3. Results

We modelled company financial distress using CART, CHAID, and C5.0 algorithms based on the prepared training sample of 15,235 Slovak companies in 2019. Potential predictors of these models were nine financial ratios (see Table 1) calculated based on financial statements from 2018 together with the size and SK NACE category of these companies. All models created are compared in their predictive ability using selected characteristics (*ACC*, *TPR*, *TNR*, *PR*, *F*1, *MCC* and *AUC*) on the test sample.

In the group of CART classifiers, individual and ensemble tree models were created using bagging and boosting techniques. These binary decision trees have a maximum of five levels of division and classify the companies based on the values of seven financial ratios (*ROS*, *ROA*, *TL/SAL*, *CA/CL*, *TL/TA*, *CASH/TA*, and *SAL/TA*) together with the size and SK NACE categories. As can be seen in Table 2, the ensemble models achieved better results compared to the individual CART model. The best results were achieved by the CART_boost model, which correctly identified impending financial distress in more than 84% of non-financial-distressed companies.

Table 2. Predictive ability of CART models

Measure	CART_indiv	CART_boost	CART_bagg
ACC	87.18%	88.11%	88.19%
TPR	81.60%	84.14%	83.71%
TNR	92.83%	92.13%	92.72%
PR	92.01%	91.54%	92.09%
*F*1	86.49%	87.68%	87.70%
MCC	0.749	0.765	0.767
AUC	0.916	0.926	0.924

Another group of created models consists of decision trees of the CHAID type. These trees are not binary, and a maximum of three division levels have been set to only three levels. Again, an individual CHAID classifier was created and bagging and boosting ensemble classifiers. The CHAID trees classify companies based on the values of the same predictors as the CART trees except for the SK NACE category. These models are much more complex compared to CART models. Nevertheless, they achieve a similar predictive ability (see Table 3). In this case, the boosting and bagging models achieved comparable results and outperformed the individual model.

The last model is the decision tree generated by algorithm C5.0. For specifics of this algorithm, the individual model is already very complex, and combined models of this type were created. The resulting model consists of 53 nodes in 10 division levels and employs all potential predictors. The C5.0 model reaches only the average overall accuracy *ACC* = 87.12% compared to other models. However, the model has the most balanced predictive ability, as it correctly classified *TNR* = 88.92% of financial-distressed companies and *TPR* = 85.35% of non-financial-distressed companies, which is the highest value of all created models. Other quality characteristics are comparable to the results of the CART and CHAID models.

Table 3. Predictive ability of CHAID models

Measure	CHAID_indiv	CHAID_boost	CHAID_bagg
ACC	86.25%	86.88%	86.86%
TPR	82.92%	84.35%	83.40%
TNR	89.61%	89.45%	90.36%
PR	88.99%	89.01%	89.76%
*F*1	85.85%	86.61%	86.46%
MCC	0.727	0.739	0.739
AUC	0.938	0.946	0.944

4. Discussion

Financial status prediction is a complex issue explaining the way of corporate governance in various aspects such as working capital management, debt management, earnings management, and others in Central Europe. Many scientific outputs contribute to current theoretical and empirical knowledge about estimating a company's financial distress using a wide range of statistical-analytical approaches such as discriminant analysis, logistic regression, decision trees, neural networks, and others to provide a predictive model with excellent statistical metrics focusing on the successful classification of non-financial-distressed enterprises. These steps lead to eliminating potential economic and social damage at the national and international levels. Financial health as a part of risk man-agement dealing with Slovak companies are analyzed by Brozyna et al. (2016), Kovacova and Kliestik (2017), Valaskova et al. (2018), Civelek et al. (2020), Csikosova et al. (2020), Gre-gova et al. (2020), Horak et al. (2020), Jenčová et al. (2020), and Svabova et al. (2020). Horváthová and Mokrišová (2020) believe that data envelopment analysis is a suitable alternative method for assessing the financial health of companies compared to other methods.

We estimate the financial distress of Slovak companies using several decision tree algorithms. All created models achieved comparable results in the overall accuracy as well as other characteristics of the overall quality of the models. However, CART type classification trees achieved the best results, especially as combined classifiers. Overall, the best is the CART_boost model – a binary tree classifier created using the boosting technique.

From the point of view of sensitivity (*TPR*), the best tree model is created by the C5.0 growth algorithm because this model outperforms other models in the classification ability in the group of non-financial-distressed companies. In other words, the model best predicts the impending financial problems of Slovak companies. In addition, it is an individual decision tree, which is relatively easy to implement in practice for a set of simple rules. We find that 9 out of 25 indicators are a suitable input for estimating financial distress, especially profitability and indebtedness indicators. Similarly, Jan (2021) selected important indicators for assessing financial failure using CHAID. It identified nine out of 23 such as debt ratio, EPS, audited by BIG4, operating income ratio, cash flow ratio, times interest earned, D/E ratio, long-term liability ratio and shareholders' equity, and gross margin. These indicators were applied in creating an effective prediction model using two deep learning algorithms such as deep neural networks (DNN) and convolutional neural networks (CNN). However, this research focuses on listed companies.

Our research offers a prediction model for Slovak companies in all industries, unlike Štefko et al. (2020) and Jenčová et al. (2020). Štefko et al. (2020) estimate the financial distress of Slovak companies dealing with the heating industry using data envelopment analysis. Furthermore, Jenčová et al. (2020) model the financial health of electrical engineering companies using binary logistic regression. Return on sales, quick ratio, and networking capital ratio are important indicators reducing the likelihood of bankruptcy.

Limitations. The models do not consider the impact of the COVID-19 pandemic because they were created using pre-pandemic data from 2018 and 2019. Therefore, their actual use in the current pandemic situation may be limited. Also, the models were designed to predict the financial distress of Slovak companies. Therefore, it is necessary to verify their use in other similar countries.

Future research. These results are part of long-term research on predicting the financial stability of Slovak companies from various industries to identify the key variables dividing companies into financial-distressed and non-financial-distressed. This research represents a potential step for future research on applying neural networks in risk management using statistically significant indicators resulting from the presented research. We plan to use the current results to apply neural networks to provide a model with even better performance metrics in future research.

Conclusions

We focused on modelling the financial distress of Slovak companies using decision trees generated by CART, CHAID, and C5.0 algorithms. Individual decision trees were created using bagging and boosting techniques, and ensemble tree classifiers were also created. As a result, the models achieved relatively high predictive power. However, it is necessary to verify their predictive ability on more relevant data affected by the COVID-19 pandemic.

Funding

The paper is funded by the Scientific Grant Agency of the Ministry of Education, Science, Research and Sports of the Slovak Republic and the Slovak Academy of Sciences [grant numbers 1/0166/20, 1/0157/21].

Disclosure statement

The authors declare no conflict of interest.

References

Andreica, M. E. (2012). Financial distress prediction of the Romanian companies using CHAID models. *Metalurgia International*, *17*(12), 196–200.

Ashoori, S., & Mohammadi, S. (2011). Compare failure prediction models based on feature selection technique: Empirical case from Iran. *Procedia Computer Science*, *3*, 568–573. https://doi.org/10.1016/j.procs.2010.12.094

Berent, T., Bławat, B., Dietl, M., Krzyk, P., & Rejman, R. (2017). Firm's default – New methodological approach and preliminary evidence from Poland. *Equilibrium*, *12*(4), 753–773. https://doi.org/10.24136/eq.v12i4.39

Brozyna, J., Mentel, G., & Pisula, T. (2016). Statistical methods of the bankruptcy prediction in the logistic sector in Poland and Slovakia. *Transformations in Business & Economics*, *15*(1(37)), 93–114.

Chandra, D. K., Ravi, V., & Bose, I. (2009). Failure prediction of dotcom companies using hybrid intelligent techniques. *Expert Systems with Applications*, *36*(3), 4830–4837. https://doi.org/10.1016/j.eswa.2008.05.047

Chen, M.-Y. (2012). Comparing traditional statistics, decision tree classification, and support vector machine techniques for financial bankruptcy prediction. *Intelligent Automation & Soft Computing*, *18*(1), 65–73. https://doi.org/10.1080/10798587.2012.10643227

Chen, S. (2016). Detection of fraudulent financial statements using the hybrid data mining approach. *SpringerPlus*, *5*(1), 89. https://doi.org/10.1186/s40064-016-1707-6

Civelek, M., Kiju, A., Vavre, V., & Gajdka, K. (2020). The Usage of technology-enabled marketing tools by SMEs and their bankruptcy concerns: Evidence from Visegrad countries. *Acta Montanistica Slovaca*, *25*. https://doi.org/10.46544/AMS.v25i3.01

Csikosova, A., Janoskova, M., & Culkova, K. (2019). Limitation of financial health prediction in companies from post-communist countries. *Journal of Risk and Financial Management*, *12*(1), 15. https://doi.org/10.3390/jrfm12010015

Csikosova, A., Janoskova, M., & Culkova, K. (2020). Application of discriminant analysis for avoiding the risk of quarry operation failure. *Journal of Risk and Financial Management*, *13*(10), 231. https://doi.org/10.3390/jrfm13100231

Delen, D., Kuzey, C., & Uyar, A. (2013). Measuring firm performance using financial ratios: A decision tree approach. *Expert Systems with Applications*, *40*(10), 3970–3983. https://doi.org/10.1016/j.eswa.2013.01.012

Durica, M., Frnda, J., & Svabova, L. (2019). Decision tree-based model of business failure prediction for Polish companies. *Oeconomia Copernicana*, *10*(3), 453–469. https://doi.org/10.24136/oc.2019.022

Gregova, E., Valaskova, K., Adamko, P., Tumpach, M., & Jaros, J. (2020). Predicting financial distress of slovak enterprises: Comparison of selected traditional and learning algorithms methods. *Sustainability*, *12*(10), 3954. https://doi.org/10.3390/su12103954

Horak, J., Krulicky, T., Rowland, Z., & Machova, V. (2020). Creating a comprehensive method for the evaluation of a company. *Sustainability*, *12*(21), 9114. https://doi.org/10.3390/su12219114

Horváthová, J., & Mokrišová, M. (2020). Comparison of the results of a data envelopment analysis model and logit model in assessing business financial health. *Information*, *11*(3), 160. https://doi.org/10.3390/info11030160

Jabeur, S. B., & Fahmi, Y. (2018). Forecasting financial distress for French firms: A comparative study. *Empirical Economics*, *54*(3), 1173–1186. https://doi.org/10.1007/s00181-017-1246-1

Jan, C. (2018). An effective financial statements Fraud detection model for the sustainable development of financial markets: Evidence from Taiwan. *Sustainability*, *10*(2), 513. https://doi.org/10.3390/su10020513

Jan, C. (2021). Financial Information asymmetry: using deep learning algorithms to predict financial distress. *Symmetry*, *13*(3), 443. https://doi.org/10.3390/sym13030443

Jayasekera, R. (2018). Prediction of company failure: Past, present, and promising directions for the future. *International Review of Financial Analysis*, *55*, 196–208. https://doi.org/10.1016/j.irfa.2017.08.009

Jenčová, S., Štefko, R., & Vašaničová, P. (2020). Scoring Model of the financial health of the electrical engineering industry's non-financial corporations. *Energies*, *13*(17), 4364. https://doi.org/10.3390/en13174364

Korol, T. (2019). Dynamic Bankruptcy prediction models for European enterprises. *Journal of Risk and Financial Management*, *12*(4), 185. https://doi.org/10.3390/jrfm12040185

Kovacova, M., & Kliestik, T. (2017). Logit and Probit application for the prediction of bankruptcy in Slovak companies. *Equilibrium*, *12*(4), 775–791. https://doi.org/10.24136/eq.v12i4.40

Li, H., Sun, J., & Wu, J. (2010). Predicting business failure using classification and regression tree: An empirical comparison with popular classical statistical methods and top classification mining methods. *Expert Systems with Applications*, *37*(8), 5895–5904. https://doi.org/10.1016/j.eswa.2010.02.016

Nyitrai, T., & Virág, M. (2019). The effects of handling outliers on the performance of bankruptcy prediction models. *Socio-Economic Planning Sciences*, *67*, 34–42. https://doi.org/10.1016/j.seps.2018.08.004

Popescu, M. E., Andreica, M., & Popescu, I.-P. (2017). Decision Support solution to business failure prediction. *Proceedings of the International Management Conference*, *11*(1), 99–106.

Popescu, M. E., & Dragotă, V. (2018). What Do post-communist countries have in common when predicting financial distress? *Prague Economic Papers*, *27*(6), 637–653. https://doi.org/10.18267/j.pep.664

Popescu, M. E., & Paun, R.-M. (2016). Prediction Models for high versus less performant economies in the European Union. In M. H. Bilgin & H. Danis (Eds.), *Entrepreneurship, Business, and economics – Vol. 2* (pp. 307–317). Springer International Publishing. https://doi.org/10.1007/978-3-319-27573-4_21

Manogna, R. L., & Mishra, A. K. (2021). Measuring financial performance of Indian manufacturing firms: Application of decision tree algorithms. *Measuring Business Excellence*. https://doi.org/10.1108/MBE-05-2020-0073

Štefko, R., Horváthová, J., & Mokrišová, M. (2020). Bankruptcy prediction with the use of data envelopment analysis: An empirical study of Slovak businesses. *Journal of Risk and Financial Management*, *13*(9), 212. https://doi.org/10.3390/jrfm13090212

Svabova, L., Michalkova, L., Durica, M., & Nica, E. (2020). Business failure prediction for Slovak Small and Medium-Sized Companies. *Sustainability*, *12*(11), 4572. https://doi.org/10.3390/su12114572

Valaskova, K., Kliestik, T., & Kovacova, M. (2018). Management of financial risks in Slovak enterprises using regression analysis. *Oeconomia Copernicana*, *9*(1), 105–121. https://doi.org/10.24136/oc.2018.006

Wieprow, J., & Gawlik, A. (2021). The use of discriminant analysis to assess the risk of bankruptcy of enterprises in crisis conditions using the example of the tourism sector in Poland. *Risks*, *9*(4), 78. https://doi.org/10.3390/risks9040078

Zięba, M., Tomczak, S. K., & Tomczak, J. M. (2016). Ensemble boosted trees with synthetic features generation in application to bankruptcy prediction. *Expert Systems with Applications*, *58*, 93–101. https://doi.org/10.1016/j.eswa.2016.04.001