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Country-specific financial distress prediction using decision trees: Empirical evidence from Slovakia and Croatia

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Abstract. This paper develops and compares financial distress (FD) prediction models for Slovak and Croatian firms based on a decision tree (DT) approach. The study aims to identify the crucial financial variables that predict firm FD in these two post-transition economies that share historical and institutional similarities but differ in the structure of the economy. A database of Slovak and Croatian enterprises was analysed, focusing on firms being classified as prosperous or non-prosperous based on standardized accounting parameters from financial reports. DTs were employed since they can model complex, nonlinear relationships without diminishing interpretability. The results indicate that high levels of total indebtedness, equity leverage, and debt-to-equity ratios are cross-sectionally associated with an increased likelihood of FD. In the Slovak context, liquidity, particularly the current ratio, showed greater importance than profitability measures, whereas in Croatia profitability ratios, especially return on assets, gained relatively higher relevance compared to liquidity. The findings close a research gap concerning country-specific differences in Central and Eastern European (CEE) FD predictors. The paper provides theoretical contributions by refining knowledge on insolvency drivers in post-transition economies and practical contributions by understanding tailored early warning systems. The study is limited by sample restrictions and the omission of macroeconomic factors. Future research may incorporate wider contextual determinants and alternative machine learning (ML) approaches.

Keywords: financial distress prediction, decision trees, financial distress, firm-level analysis, post-transition economies

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1. Introduction

Financial distress (FD) prediction remains a central topic in financial and economic research due to its implications for corporate governance, financial stability, and regulatory oversight [18, 38]. The increasing demand for reliable early-warning systems has intensified the search for accurate yet interpretable predictive models. This is particularly relevant for countries in Central and Eastern Europe (CEE), where the legacy of centrally planned economies, the post-transition reforms, and the gradual integration into European institutional frameworks have created unique patterns of corporate FD. Among these countries, Slovakia and Croatia offer a compelling comparison due to their shared post-socialist history and European Union (EU) membership, yet also notable differences in macroeconomic trajectories, sectoral structures,

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and institutional maturity. Slovakia is more manufacturing- and export-oriented, with deeper integration into European value chains and higher credit penetration, whereas Croatia has a larger share of small and medium-sized enterprise (SMEs) and relies more heavily on service-based sectors such as tourism. These structural differences may influence the role of specific predictors, as liquidity shortages are often more pressing in SME-dominated economies, while profitability indicators tend to be more relevant in investment- and export-driven contexts. In both Slovakia and Croatia, the prediction and management of corporate FD have gained increasing policy relevance over the past two decades. Following the transition to market economies, insolvency frameworks and financial reporting standards have gradually aligned with EU regulations, improving transparency and enabling more systematic firm-level analysis [30, 13]. However, institutional maturity, credit availability, and sectoral dynamics continue to differ, suggesting that the explanatory power of financial ratios may not be uniform across national contexts.

Despite the progress in financial infrastructure, empirical research on FD prediction in these two countries, especially from a comparative data-driven, perspective remains limited. Much of the existing literature in the CEE region either focuses on single country analyses or applies generic models borrowed from Western contexts that may not account for the institutional and economic particularities of post-transition economies (e.g. [36, 41, 5, 43], etc). Moreover, traditional statistical techniques such as logistic regression or discriminant analysis may struggle to capture nonlinear interactions among financial variables [3]. There is thus a growing need for models that are not only empirically robust but also context-sensitive and interpretable for practical use. Recent comparative research confirms that the selection of an appropriate prediction method significantly influences classification performance and interpretability, particularly in SME and transition-economy contexts [32, 28]. Empirical evidence increasingly highlights the competitive performance of DT-based approaches in bankruptcy and FD modelling. Ďurica et al. [10] developed a decision tree (DT) model for business failure prediction in Poland and demonstrated its practical applicability in identifying high-risk firms. European evidence beyond the CEE region also indicates that DT models achieve strong predictive performance while maintaining interpretability, especially when compared with more complex artificial intelligence approaches [15, 11, 33]. These findings suggest that DT techniques represent a suitable compromise between predictive accuracy and transparency, which is particularly relevant for regulatory bodies, credit institutions, and policymakers operating in post-transition economies.

This study addresses this research gap by developing and comparing DT models for FD prediction in Slovakia and Croatia using large-scale firm-level financial data. DTs offer a compelling methodological advantage. They are capable of handling nonlinearity and interactions among predictors while preserving interpretability, an essential feature for practitioners, financial analysts, and regulatory authorities. By applying the same modelling framework to both national datasets, the study ensures comparability while allowing for the identification of both common and country-specific FD indicators. The findings demonstrate that while certain financial indicators consistently emerge as strong predictors of insolvency across different national settings, there are also meaningful variations that point to the influence of broader contextual factors. These differences likely stem from variations in financial systems, regulatory frameworks, access to credit, tax policies, and business practices, as well as sectoral compositions and macroeconomic conditions. For instance, the relative importance of liquidity, leverage, or profitability ratios may vary depending on how firms are financed, how risk is assessed by creditors, or the extent to which FD procedures are enforced. Such cross-contextual divergence underscores the importance of not relying on a one-size-fits-all model for FD prediction. Even when applying a consistent methodological framework, the predictive accuracy and relevance of specific indicators depend on the institutional and economic environment in which firms operate. This comparative approach reveals the necessity of adapting analytical models to reflect local conditions, thereby enhancing their practical applicability and robustness. It also offers valuable insights for policymakers and regulators, who may use these findings to better understand systemic risks, identify early warning signals, and design more targeted interventions to promote financial stability and corporate resilience. Ultimately, the study contributes to the broader literature on FD by demonstrating how data-driven approaches can uncover both universal patterns and context-specific nuances in financial vulnerability. To operationalize this contribution, the empirical analysis is structured around two interrelated research questions. The first addresses the identification and comparative relevance of financial indicators associated with FD risk in Slovak and Croatian firms. The second evaluates the effectiveness of DT models in classifying firms as prosperous or non-prosperous across distinct economic and institutional settings.

By focusing on Slovakia and Croatia, two EU member states at different stages of economic development within the same regional and historical framework, this paper contributes to a deeper understanding of how national contexts influence the nature and predictability of corporate FD. It extends the literature on CEE insolvency prediction by showing that the explanatory power of financial ratios is not uniform across countries, and that tailored country-specific models are necessary to capture the complexity of business failure in diverse economic systems. This study also responds to a broader theoretical and empirical gap, the underrepresentation of smaller, post-transition economies in the global FD prediction literature. While extensive research has been devoted to large economies or mature markets, CEE countries often remain peripheral in comparative modelling studies. The lack of attention to national heterogeneity not only limits the generalizability of widely used models but also underestimates the role of institutional and structural differences in shaping financial behaviour and corporate risk. By generating empirical evidence from Slovakia and Croatia and comparing results through a unified framework, this study enhances the regional understanding of insolvency drivers and offers a pathway toward more precise and effective risk assessment strategies.

In addition to its academic contributions, the findings have significant practical implications for financial institutions, credit rating agencies, policymakers, and firms themselves. Understanding the most relevant predictors of financial distress within a given national context enables the development of more accurate early warning systems, supports risk-based credit allocation, and fosters proactive regulatory oversight. As both Slovakia and Croatia continue to integrate into broader European financial markets, the ability to identify at-risk firms through data-driven interpretable models becomes increasingly important for economic resilience and sustainable growth. In summary, this paper aims to advance both the methodological frontier and the empirical understanding of FD prediction in post-transition economies. By leveraging DT models and applying them to the cases of Slovakia and Croatia, it demonstrates the importance of national specificity in predictive modelling and contributes new insights to the broader discourse on financial risk in the CEE region.

The paper is structured as follows. After the introductory part, the methodology and data section presents the development and evaluation of a predictive model for estimating corporate FD using DT algorithms. The results and discussion section evaluates the performance of DT models for predicting FD among Slovak and Croatian firms. It compares classification accuracy, variable importance, and predictive metrics across the two countries, demonstrating that while both models are highly effective, the Croatian model exhibits slightly better balance and precision, confirming the strength of machine learning (ML) approaches in national insolvency prediction. Finally, the conclusion summarizes the key findings, discusses their practical implications and suggests directions for future research.

2. Methodology and data

The empirical design relies on firm-level financial data, clearly specified classification criteria, and a unified modelling framework applied separately to Slovakia and Croatia to ensure cross-country comparability. All financial ratios were constructed in a consistent manner across both samples, and identical modelling settings were retained to preserve methodological symmetry. DT models were selected for their interpretability and capacity to capture nonlinear relationships and interaction effects among financial indicators.

2.1. Data and preprocessing

The firm-level financial data for Slovak and Croatian companies were used, extracted from the ORBIS database containing standardized financial and ownership records on enterprises worldwide. The ORBIS database was queried using predefined filters to ensure economic relevance and data consistency. The search was restricted to active companies (including those with unknown current status), excluding public authorities and government entities. Only firms with total assets exceeding EUR 200,000 and with available financial statements for recent fiscal years were retained. Companies lacking standardized financial reporting were excluded. After applying these criteria, dataset contained 27,616 Slovak and 23,565 Croatian firms. The sample includes all industries in the economy, and companies were sampled regardless of industry type, thereby ensuring adequate representation of the corporate sector in both countries. Financial ratios during 2022 were used as independent variables, whereas the dependent variable, financial stability in 2023, captures FD. To ensure data quality and consistency, firms with incomplete or missing financial data were excluded from the analysis. To minimize the effect of extreme values and the asymmetry of the distribution of financial indicators, the dataset was winsorized by the Z-score method with cutoff points at ± 3 standard deviations from the mean [48]. After preprocessing and data-cleaning procedures, the final analytical sample consisted of 4,761 Slovak and 1,186 Croatian firms, each classified as either prosperous or non-prosperous according to the defined criteria.

For model development and validation, the data were randomly divided into training (70 %) and test (30 %) sets using stratified sampling to ensure that the original distribution of class labels was preserved. The DT approach was utilized for its ability to model non-linear interactions and detect intricate interactions between financial variables with high interpretability. The choice of predictors is derived from existing empirical studies (e.g., [35, 47, 11, 8, 30, 12]). The summarized formulas of selected financial indicators are presented in Table 1.

Abbreviation	**Indicator**	**Formula**
QR	Quick ratio	Current assets minus inventories to current liabilities
CurrR	Current ratio	Current assets to current liabilities
Ins	Insolvency ratio	Total liabilities to total assets and other current assets
IT	Inventory turnover ratio	Sales to inventories
CollP	Collection period ratio	Receivables to sales (multiplied by 365 days)
CredP	Credit period ratio	Creditors to sales (multiplied by 365 days)
ROA	Return on assets ratio	Profit after tax to total assets
ROE	Return on equity ratio	Profit after tax to shareholders' funds
ROS	Return on sales ratio	Profit after tax to sales
TI	Total indebtedness ratio	Total liabilities to total assets
DE	Debt-to-equity ratio	Total liabilities to shareholders' funds
EL	Equity leverage ratio	Total assets to shareholders' funds

Table 1: *Summarized formulas of financial indicators.*

In several ratios, the denominator can take on values close to zero or even negative, most notably in the case of equity-based measures such as the equity leverage or the debt-to-equity ratios. Instead of excluding these observations or applying winsorization, such cases were retained in the dataset, as they represent genuine FD situations (e.g., firms with negative equity or excessive short-term liabilities). This approach is consistent with prior research, which emphasizes that extreme or non-standard financial ratios may carry critical information about the deteriorating financial condition of a firm. While this choice increases variance in the predictor space and may generate outliers, it was considered preferable to preserve the economic reality of the data and ensure that distress signals were not artificially suppressed. To mitigate potential issues of numerical instability, all ratios were computed consistently across firms, and their distributional properties were reviewed prior to modelling.

2.2. Classification criteria

To predict FD, the enterprises included in the model formation are categorized into two groups: prosperous enterprises with sustainable debt and non-prosperous enterprises with substantial indebtedness. The classification of firms into prosperous and non-prosperous categories follows the accounting-based distress identification framework proposed by Klieštik et al. [26], which is widely applied in Central and Eastern European insolvency research.

Condition (1): The firm reports negative equity, where the value of total liabilities (including accrued liabilities) is greater than total assets, defined as:

$$\text{Assets} - (\text{Liabilities} + \text{Accrued liabilities}) < 0 \tag{1}$$

Condition (2): If Condition (1) is violated, the firm is not thriving whenever its bonity index, an adjusted liquidity measure, is less than 1. The index is calculated as the percentage ratio of adjusted current assets to adjusted current liabilities:

$$\text{Bonity index} = \frac{\text{Adjusted Current Assets}}{\text{Adjusted Current Liabilities}} < 1 \tag{2}$$

Condition (3): When data for the bonity index are incomplete or unavailable, a simplified liquidity ratio L_3 is used instead, which sums inventories, receivables, financial assets, cash, and prepaid expenses, divided by the sum of current liabilities and accrued liabilities. The firm is non-prosperous if this ratio is less than 1:

$$L_3 = \frac{\begin{array}{c}\text{Inventories} + \text{Current Receivables} + \text{Financial Assets}\\ +\text{Cash and Equivalents} + \text{Prepaid Expenses}\end{array}}{\text{Current Liabilities} + \text{Accrued Liabilities}} < 1 \tag{3}$$

The two ratios both capture liquidity, but with the difference that the bonity index is more precise, while L_3 ensures practicability even in the instance of incomplete information.

Condition (4): The firm recorded a net loss during the observed accounting period, an indication of insufficient revenues to meet financial obligations:

$$\text{Net Profit After Tax} \leq 0 \tag{4}$$

If a firm does not meet Condition (1) of negative equity, it will still be labeled as non-prosperous if, simultaneously, it experiences inadequate liquidity, as shown by either Condition (2) or Condition (3), and reports a net loss based on Condition (4). Based on these criteria, out of 4,761 Slovak firms in the sample, 560 were classified as non-prosperous and 4,201 as prosperous. In Croatia, out of 1,186 firms, 57 were classified as non-prosperous and 1,129 as prosperous. This distribution reveals a pronounced class imbalance in both datasets, with distressed firms representing only around 12% of Slovak firms and 5% of Croatian firms.

Table 2 illustrates the distribution of firms according to the applied criteria. In Slovakia, the combination of liquidity shortfall and net loss was the most frequent driver of classification, while negative equity accounted for a smaller but still substantial share of distressed cases.

By contrast, in Croatia, negative equity was more prevalent, representing the majority of non-prosperous firms, with the remainder identified through the combined liquidity and profitability criteria. This breakdown illustrates how different mechanisms of financial fragility dominate across the two countries and confirms the complementary role of the applied conditions in capturing firm-level distress.

Classification criterion	**SK**	**HR**
Negative equity (Condition 1)	206	32
Liquidity shortfall combined with net loss (Conditions 2/3 + 4)	354	25
Total non-prosperous firms	560	57

Table 2: *Classification of non-prosperous enterprises based on criteria.*

The application of a multi-criteria approach makes it easier to identify financially distressed firms even in the absence of a court-driven FD process, thereby maintaining consistency and comparability across countries. The output Y of the model is binary classification, with 0 standing for a prosperous firm and 1 for a non-prosperous firm:

$$Y = \begin{cases} 0 & \text{for prosperous firm} \\ 1 & \text{for non-prosperous firm} \end{cases} \tag{5}$$

Although the ORBIS database provides bankruptcy event indicators, these were not used as the outcome variable. In the Slovak and Croatian context, bankruptcy filings are often underreported, delayed, or affected by institutional factors that may not adequately reflect firms' financial condition. For consistency and comparability, FD was instead operationalized through accounting-based criteria, which are commonly applied proxies in the literature. It should be noted that the classification may be sensitive to threshold choices: lowering the liquidity cutoff to 0.9 would restrict the definition of distress to more extreme cases, while raising it to 1.1 would broaden the pool of firms at risk. While such changes could affect absolute counts of distressed firms, the overall class imbalance would remain, and the relative interpretation of minority vs. majority classes would not materially change.

While these criteria are conceptually related to some predictor variables, lagged financial ratios were employed to ensure temporal separation between predictors and outcomes and to reduce concerns of circularity. The analysis was restricted to financial ratios in order to maintain methodological comparability with prior research.

2.3. Predictive modelling method

This study employs the DT model to classify enterprises into prosperous and non-prosperous ones based on their financial characteristics. DTs represent a class of supervised learning methods that recursively partition the predictor space to maximize class homogeneity. Compared to traditional linear statistical models, DTs do not require distributional assumptions, can naturally accommodate nonlinear and interaction effects among financial ratios, and remain robust in the presence of multicollinearity [40]. In addition, their hierarchical structure ensures high interpretability, allowing explicit identification of decision rules and threshold values, which is particularly relevant for early-warning applications in FD prediction.

In comparison with ensemble approaches such as random forests, single-tree models may exhibit lower predictive variance but can be more sensitive to overfitting if not properly pruned. Random forest models often achieve higher predictive accuracy due to aggregation across multiple trees. However, this comes at the cost of reduced interpretability, as the internal decision structure becomes opaque [45]. Given that the objective of this study is not only to achieve high classification performance but also to identify and compare country-specific FD determinants, interpretability was considered a primary methodological criterion. Therefore, a single DT framework was preferred over more complex ensemble techniques.

Model development is reliant on the classification and regression trees (C&RT) algorithm, where a binary recursive partitioning approach is used to split the dataset into increasingly homogeneous subgroups based on the dependent variable. In this study, the DTs were implemented in SPSS using the CRT growing method with the Gini index as the splitting criterion. The dependent variable was the binary classification of firms with or without financial difficulties, while the independent variables included a set of financial ratios.

For each node, the algorithm examines all possible splits on each predictor and selects the one that results in the most dissimilar child nodes in terms of class membership. In the SPSS C&RT procedure, default hyperparameters were retained: a maximum tree depth of 5, a minimum of 10 cases in parent nodes, and a minimum of 5 cases in child nodes. Pruning was performed automatically by the software to avoid overfitting.

To make the best splits, the algorithm attempts to minimize impurity and to perform this minimization, and it applies the Gini index, a standard measure that approximates node heterogeneity. The Gini index is defined as:

$$\text{Gini} = 1 - \sum_{i=1}^{C} (p_i)^2 \tag{6}$$

where p_i is the likelihood that an observation at random is in category i, and C is the number of categories. A node can be considered pure when all observations in it are from one class, indicating that the Gini index equals zero. The algorithm seeks to create nodes of minimum impurity [29]. Prior comparative studies in bankruptcy prediction demonstrate that DT-based models achieve competitive predictive performance relative to neural networks and support vector machines, particularly when interpretability is required [6, 11]. In several Central and Eastern European applications, DT models have reported classification accuracies exceeding 90%, confirming their empirical robustness in insolvency modelling contexts [12]. One of the main advantages of DTs is their ability to automate variable selection in tree construction. Irrelevant and poor predictors are automatically eliminated, reducing model complexity and making it easier to interpret. This is particularly valuable in high-dimensional financial data, where multicollinearity and noise would stop optimal performance in conventional statistical models. Predictor importance was derived from the reduction in Gini impurity aggregated across all splits where a variable was used. These importance values were later reported in the results to identify the financial ratios most relevant to predicting FD.

To mitigate overfitting risk, pruning procedures were applied within the CRT framework to ensure generalizability of the final model. The DT is trained on a 70 % stratified training sample, while predictive performance was evaluated on the remaining 30 % test set using standard classification metrics.

2.4. Model evaluation metrics

The predictive performance of DT models was assessed through three popular classification measures: AUC, accuracy, and F1 score. AUC indicates how well the model can discriminate between prosperous and non-prosperous firms at various classification thresholds, with values closer to 1 indicating higher discrimination power. Accuracy computes the overall ratio of correctly predicted instances and provides a straightforward measure of correctness. The F1 score, the harmonic mean of recall and precision, is particularly beneficial in imbalanced datasets, balancing the false positive and true negative trade-offs with more sensitivity than accuracy by itself. According to Berrada et al. [7], these metrics provide an integrated measurement framework for FD models. All classification performance metrics (precision, recall, F1 score, and AUC) are evaluated with respect to the minority class of non-prosperous firms, which represents the event of interest in FD prediction.

3. Results and discussion

Table 3 summarises the classification performance of the DT models for Slovakia and Croatia. In both countries, the models classify prosperous firms with very high accuracy. In Slovakia, 99.6% of prosperous firms are correctly classified in the training sample and 99.3% in the test sample, while the identification of non-prosperous firms reaches only 15.4% and 24.2%, respectively. The overall test accuracy is 91.26%. In Croatia, the model correctly classifies 98.5% of prosperous firms in training and 99.7% in testing, whereas the identification of distressed firms improves to 46.3% and 50.0%. The overall test accuracy reaches 97.38%.

Classification							
		SK			**HR**		
Sample	**Observed**	**Predicted**		**Percent**	**Predicted**		**Percent**
		0	**1**	**Correct**	**0**	**1**	**Correct**
Training	0	2,928	13	99.6%	790	12	98.5%
	1	330	60	15.4%	22	19	46.3%
	Overall Percent	97.8%	2.2%	89.7%	96.3%	3.7%	96.0%
Testing	0	1,268	9	99.3%	326	1	99.7%
	1	116	37	24.2%	8	8	50.0%
	Overall Percent	96.8%	3.2%	91.3%	97.4%	2.6%	97.4%

Table 3: *Classification performance of DT models for Slovakia and Croatia.*

Given the pronounced class imbalance, where non-prosperous firms represent only around 5–11% of observations, overall accuracy is largely driven by the majority class (Table 4). The Croatian model achieves a higher discriminatory power, with an AUC of 0.922 compared to 0.861 in Slovakia. Precision remains high in both countries, however, recall is substantially stronger in Croatia, resulting in a higher F1 score. Overall, the Croatian model provides a more balanced early-warning performance, whereas the Slovak model remains more biased toward the majority class.

Country	**AUC**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
SK	0.861	0.9126	0.8043	0.2418	0.3719
HR	0.922	0.9738	0.8889	0.5000	0.6400

Table 4: *Prediction results and models accuracy for Slovakia and Croatia.*

The relatively low recall confirms that model performance is constrained by the minority representation of non-prosperous firms. While overall accuracy and precision remain high, these metrics are largely driven by the dominant class of prosperous enterprises. This pattern is consistent with prior FD prediction research and reflects the inherent difficulty of early-warning modelling under imbalanced data conditions. Future methodological refinements, such as resampling strategies or cost-sensitive learning approaches, may help improve the detection rate of distressed firms.

These findings compare to or surpass those of comparable benchmarks in earlier Slovak research. Adamko and Švábová [1] constructed Altman-based logistic models with 0.81-0.88 AUC scores, reiterating high discriminatory power. Conversely, Gregová et al. [19] and Horváthová et al. [22] confirmed that ANN operated with 94.37% and 95.45% accuracy, respectively. Ďurica et al. [11] were slightly more precise in their findings, employing ANN (96.5%) and DT (93.2%) models, although their data horizon was shorter. Horák et al. [21], employing a mixed evaluation approach with both financial and non-financial performance indicators, applied artificial neural networks and logistic regression models. Their results showed overall accuracy close to 81%, with higher accuracy (almost 90%) for firms surviving FD, but considerably lower accuracy (around 55%) for identifying firms at risk of bankruptcy. In this case, the performance of the developed model reaches 91.26% accuracy and an AUC of 0.861. While competitive in terms of overall accuracy compared to past Slovak studies, its recall is modest (24.18%), underscoring the challenge of early-warning performance under class imbalance.

In the Croatian context as well, the DT model of this study is much improved over past national endeavors. Such past models used to perform inadequately at lower-quality categorizations or possess limited generalizability. Zenzerović [46] achieved 95.3% accuracy using multiple discriminant analysis (MDA), but from the estimation sample only, limiting its external validity. Bogdan [9] applied logistic regression to the restaurant industry to achieve 82.8% accuracy, whereas Pervan et al. [34] achieved merely 76.3% on a larger dataset. In that context, the Croatian DT model achieved 97.38% accuracy and an AUC of 0.922, with a precision of 88.89% and recall of 50.00% for distressed firms. Some recent Croatian studies extend FD prediction beyond traditional financial ratios. In addition, Galant and Zenzerović [17] examined the role of corporate social responsibility, highlighting the potential relevance of non-financial determinants in distress modelling. Although such variables are not incorporated in the present study, their inclusion may represent a promising direction for future research aimed at enriching firm-level prediction frameworks. Arnerić and Moćan [4] applied Bayesian logistic regression to predict bankruptcy in trading companies under uncertainty, reporting high predictive accuracy and strong identification of distressed firms compared to conventional approaches.

The structure of the trained DT models reflects the hierarchical importance of selected financial indicators identified during model estimation. A graphical representation of the full tree structures is provided in the online supplementary material [16]. The relative importance of independent variables to predict FD using DT models exhibits both consistent patterns and profound national differences (Table 5). For both countries, total indebtedness, equity leverage, and debt-to-equity ratio are rated as the most significant predictors with importance values of close to or exactly 100%. These ratios collectively capture the leverage position and corporate capital structure, underlining their central role in FD prediction. In the Slovak model, among liquidity measures, the current ratio emerges as one of the most important variables, exceeding the predictive relevance of profitability indicators. Profitability ratios, especially return on assets, followed by return on equity and return on sales, also contribute meaningfully to classification performance, although to a lesser extent. Additional liquidity and solvency indicators, including the quick ratio and insolvency ratio, further support the differentiation between prosperous and non-prosperous firms. These findings suggest that capital structure and short-term liquidity conditions play a dominant role in explaining FD risk in Slovakia, while profitability measures provide complementary explanatory power. In contrast, the Croatian model is primarily driven by leverage-related indicators, with total indebtedness, debt-to-equity, and equity leverage emerging as the most influential predictors. Beyond leverage, return on assets and the current ratio show substantial predictive importance, followed by return on sales and return on equity. The insolvency ratio exhibits only marginal relevance, while the quick ratio and turnover-based variables contribute negligibly to classification performance. Overall, while leverage-related metrics are consistently central across both countries, the Slovak model places relatively stronger emphasis on liquidity conditions, particularly the current ratio, whereas the Croatian model assigns comparatively greater relevance to profitability indicators.

The findings of FD prediction models for Croatian and Slovak enterprises corroborate the established applicability of leverage ratios as primary drivers of FD, consistent with earlier empirical research in these countries and Europe. In the Slovak context, the total indebted-

Independent variable importance				
	SK		HR	
Variable	Importance	Percent	Importance	Percent
Quick ratio	0.008	21.7%	0.000	0.0%
Current ratio	0.019	50.3%	0.006	26.2%
Insolvency ratio	0.007	18.5%	0.000	1.3%
Inventory turnover ratio	0.002	5.2%	0.000	0.0%
Collection period ratio	0.000	1.1%	0.000	0.0%
Credit period ratio	0.002	4.7%	0.000	0.1%
Return on assets ratio	0.017	45.1%	0.010	41.8%
Return on equity ratio	0.013	35.0%	0.003	10.6%
Return on sales ratio	0.013	35.1%	0.004	16.4%
Total indebtedness ratio	0.037	100.0%	0.024	100.0%
Debt-to-equity ratio	0.037	97.7%	0.023	96.5%
Equity leverage ratio	0.037	97.7%	0.023	96.5%

Table 5: *Independent variable importance in DT models for Slovakia and Croatia.*

ness ratio is the most prevailing variable, consistent with Mihalovič [31] and Horváthová et al. [23], both of which analysed Slovak companies, and similarly identified leverage measures as primary in artificial neural network (ANN) models. The extremely high importance of the debt-to-equity ratio is also in agreement with findings by Korol [27], focused on Central and Eastern Europe, and Behr and Weinblat [6], who examined German enterprises using machine learning methods including DTs and pointed to its central role in ML models of FD prediction. Concerning liquidity, the importance of current ratio in Slovakia validates research by Radovanovic and Haas [37] on European enterprises and Slovak-specific research by Weiss et al. [44], and Jenčová et al. [24] that liquidity is a significant but secondary factor after leverage. However, when comparing individual indicators, profitability ratios rank higher than quick and insolvency ratios, which suggests that profitability plays a more consistent role than some liquidity measures. This pattern indicates that liquidity ratios are crucial in ascertaining the short-term ability of a firm to settle its immediate financial obligations, but profitability also provides an important complementary signal of financial health. Firms with low liquidity are more vulnerable to cash flow disruptions that can rapidly aggravate FD. The moderate importance of profitability ratios echoes the same research and regional studies, such as Tudor et al. [42] focused on Romania, implying a complementary yet less determining role in prediction. Operating and insolvency-based ratios were not influential, consistent with the prior literature that these variables generally have limited contributions compared to basic financial health indicators.

For Croatian firms, leverage ratios again emerge as premier predictors, consistent with overall European results presented by Behr and Weinblat [6] as well as by Pervan et al. [35], who used logit models on Croatian enterprises, and Žiković [47], who employed discrete-time hazard models. The relatively weaker importance of liquidity and profitability ratios compared to Slovakia can be attributed to structural and economic differences within the Croatian corporate sector. Croatia's economy, having a larger share of SMEs and industries with distinctive financial profiles, may experience different patterns of FD where liquidity shortages are less prominent or manifest in unique ways. Specifically, according to European Commission data [14], the SME share of value added is higher in Croatia than in Slovakia, while the credit-to-GDP ratio is markedly lower, indicating more limited access to bank financing. These structural conditions help explain why leverage indicators dominate in Croatia, whereas liquidity indicators retain greater importance in Slovakia. Institutional settings further reinforce these differences, as variations in restructuring and liquidation frameworks across CEE significantly influence the detection and management of FD [25]. Similarly, comparative research on SME-led growth in

Adriatic economies highlights the distinct weight of smaller firms in Croatia's economy [20], which can amplify the reliance on leverage-based indicators. Furthermore, regulatory and market conditions, including access to credit and alternative bankruptcy proceedings, can influence which financial ratios are most predictive of distress. The marginal impact of operating performance ratios and interest coverage ratios in our Croatian model also aligns with Mihalovič [31] that these variables have limited use in this specific setting. Such contextual factors underscore the need to tailor bankruptcy prediction models to the country-specific institutional setting and firm characteristics to increase their practical relevance and accuracy. Previous research on Croatian firms has highlighted the relevance of macroeconomic and institutional factors in explaining FD dynamics [47, 2, 39]. Although the present study focuses exclusively on firm-level financial indicators, these findings suggest that incorporating macro-level determinants may further enhance distress prediction models and represents a promising direction for future research.

Together with these results, the outcomes of prior Slovak and Croatian studies employing ML approaches validate the increasing dominance of ML methods over traditional ones in FD prediction in Slovakia and Croatia. Previous work using MDA or logistic regression [4] showed acceptable yet comparatively weaker results. ANN and DT models [11, 12] have, however, surpassed these benchmarks, with several of them exceeding 90% accuracy. The developed DT models achieve competitive performance relative to these benchmarks, particularly in terms of overall accuracy and discriminatory power. This finding further supports the growing application of interpretable ML techniques in insolvency prediction.

4. Conclusions

This study develops and cross-compares FD prediction models for Slovak and Croatian firms, two CEE economies that remain relatively underrepresented in insolvency research. The findings confirm the dominant role of leverage indicators, particularly total indebtedness and debt-to-equity ratios, in both countries. At the same time, important country-specific differences emerge. In Slovakia, liquidity, especially the current ratio, provides substantial complementary predictive power alongside leverage, while in Croatia profitability ratios, particularly return on assets, assume relatively greater importance compared to liquidity measures. These results deepen the understanding of how institutional and structural differences shape the explanatory power of financial ratios and highlight the need for country-specific FD modelling frameworks.

From a practical perspective, the results provide relevant guidance for financial analysts, credit institutions, and policymakers by identifying key financial indicators for early-warning monitoring. The interpretability of DT models enhances their practical usability, as decision rules and threshold values can be transparently communicated and applied in risk assessment processes. The observed cross-country variation further suggests that predictive systems should reflect national economic structures and regulatory environments rather than rely on universal ratio hierarchies.

Several limitations should be acknowledged. The models rely exclusively on accounting-based financial data and therefore do not capture qualitative determinants such as management quality, governance structure, or market-specific shocks. The analysis is restricted to two countries, which limits broader generalization across the CEE region. Moreover, FD is operationalized through accounting-based criteria rather than observed bankruptcy events, and the pronounced class imbalance constrains recall despite high overall accuracy. The models were estimated using default hyperparameter settings and were not systematically benchmarked against alternative ML or regression-based approaches. Future research should therefore incorporate non-financial and macroeconomic determinants, explore cost-sensitive or optimized modelling strategies, and extend the analysis across additional countries and time horizons to strengthen robustness and external validity.

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