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Article

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Article

Bankruptcy Prediction, Financial Distress and Corporate Life Cycle: Case Study of Central European Enterprises

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Abstract: Businesses are influenced by the cyclical nature of economic development and distinct stages in the corporate life cycle. Accurate early-warning mechanisms are crucial to mitigating bankruptcy risk, enabling timely rescue measures. This article analyses the reliability of various bankruptcy prediction models, including those by Klietnik et al., Poznanski, the modified Zmijewski, Jakubik–Teply, and Virag–Hajdu, across corporate life cycle stages. Reliability was assessed using five metrics: accuracy, balanced accuracy, *F1* and *F2* scores, and the Matthews correlation coefficient (*MCC*). The sample included over 5000 SMEs from Central Europe, with financial data from 2022. The findings reveal a U-shaped trend in financial distress risk, with start-ups and declining enterprises facing the highest risks. The results indicate that the Klietnik et al. model shows consistent reliability across all life cycle stages, while the Poznanski model shows more variability. Conversely, the Virag–Hajdu model exhibits significant variability in reliability, with its best performance observed during the Decline stage. The modified Zmijewski and Jakubik–Teply models show lower *MCC* values overall, with the modified Zmijewski model performing better at predicting the financial distress of mature shake-out firms compared to other stages.

Keywords: financial distress; corporate life cycle; reliability of model



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1. Introduction

In recent years, both the global and European economies have undergone several significant upheavals. Since the onset of the COVID-19 pandemic and the subsequent lockdowns, coupled with the energy crisis and rising inflation, concerns about insufficient economic growth and the potential for a subsequent recession have intensified. Businesses have faced—and continue to face—disproportionate pressure to achieve satisfactory financial results despite adverse economic conditions. An important factor in attaining economic stability, in addition to external economic conditions, is the set of internal factors that characterise a company's life cycle.

The corporate life cycle is a foundational construct in management sciences (Miller & Friesen, 1984) and corporate finance (Anthony & Ramesh, 1992). Originating from product life cycle theories, it acknowledges that companies, unlike products, are subject to a broader array of influences, rendering product-based analytical models insufficient. Miller and Friesen (1984) contend that the progression through life cycle stages is driven by internal determinants, such as managerial competencies, financial capacities, and performance metrics, as well as external forces like macroeconomic dynamics and competitive landscapes. Dickinson (2011) advances this understanding by highlighting the interdependence between strategic orientation and resource allocation, underscoring that

life cycle phases are distinguishable by their unique cash flow configurations. [Damodaran \(2018\)](#) observes that nascent firms depend heavily on external financing sources, including bank loans, venture capital, and trade credit, owing to constrained internal resources. Internal financing becomes viable in later stages, with debt accumulation closely linked to sales growth and profitability, driven by the associated tax advantages. During maturity, stabilised profits and cash flows reduce anticipated bankruptcy costs, facilitating the distribution of dividends beginning in the maturity phase.

Understanding the financial health of firms across these stages is critical, as early-stage companies are exposed to pronounced credit risk and volatility in earnings and cash flows ([Habib & Hasan, 2017](#)). As firms progress, the Growth phase mitigates these risks, fostering profitability and diminishing reliance on debt. Mature firms attain peak operational stability and gravitate towards internal financing, often under shareholder pressure to maintain dividend payouts. Shake-out firms experience eroding profitability and may either restructure or downscale operations. Declining firms face reduced production capabilities, negative operating cash flows, and low earnings, frequently resorting to tax avoidance strategies or earnings management to alleviate financial distress ([Edwards et al., 2016](#); [Hussain et al., 2020](#)).

[Amin et al. \(2023\)](#) investigated the relationship between a firm's life cycle stage and its cost of debt, concluding that younger firms incur higher lending spreads compared to their mature and older counterparts. [Ngo et al. \(2023\)](#) examined the nexus between financial distress, life cycle stages, and cash holdings. Their study revealed that firms in early life cycle stages, such as introduction and growth, maintain lower cash reserves, while cash holdings increase as firms mature. Financial distress, however, is more pronounced in the early stages, driven by liquidity constraints and restrictive debt obligations.

Early identification of financial distress is essential for mitigating risks and ensuring business continuity ([Beaver, 1966](#)). Financial distress—defined as a transitional state between solvency and insolvency—has significant implications for firms, creditors, and stakeholders ([Purnanandam, 2008](#)). The foundational Altman Z-score model ([Altman, 1968](#)) continues to be a key element in this area, yet later advancements have led to more refined methods designed for industries, geographical areas, and company traits ([Kliestik et al., 2020](#); [Voda et al., 2021](#); [Kozel et al., 2022](#); [Grice & Dugan, 2003](#)). Despite these advancements, there is a notable gap in the literature concerning the application of bankruptcy prediction models to different stages of the corporate life cycle. Addressing this gap is crucial, as firms at various life cycle stages exhibit distinct financial profiles and risks.

This article aims to analyse and evaluate the reliability of selected bankruptcy prediction models across the corporate life cycle. A sample of Central European small and medium-sized manufacturing enterprises (NACE category C) for the year 2022 was used, comprising over 5000 firms. Sub-samples were created based on country of origin and life cycle stages, as defined by [Dickinson's \(2011\)](#) cash flow model. Selected models include the Poznanski model ([Wieprow & Barlik, 2017](#)), the Jakubik–Teply model ([Jakubik & Teply, 2011](#)), the Virag–Hajdu model ([Virag & Hajdu, 1996](#)), and the Kliestik et al. model for SMEs ([Kliestik et al., 2018](#)). The modified Zmijewski model by [Grice and Dugan \(2003\)](#), which detects financial distress risk, was also included. The confusion matrix methodology and its metrics were employed to evaluate model reliability, focusing on robust metrics like balanced accuracy, *F1* and *F2* scores, and the Matthews correlation coefficient (*MCC*). These metrics address imbalances in sample size and class distribution, ensuring comprehensive evaluation.

By bridging the gap in the understanding of the interaction between corporate life cycle stages and bankruptcy prediction models, this research contributes to both theoretical

and practical advancements. It provides valuable insights for academics studying financial stability and practitioners managing corporate risks.

2. Literature Review

The corporate life cycle is a theoretical construct widely utilised to analyse the evolution of firms through distinct developmental stages. [Dickinson \(2011\)](#) delineates five stages in the corporate life cycle: Introduction, Growth, Maturity, Shake-out, and Decline. Each stage is characterised by distinct combinations of operational, investment, and financial cash flows. In the Introduction phase, firms predominantly utilise external financing and confront elevated risk levels due to negative operating cash flows and substantial investment expenditures ([Damodaran, 2018](#)). The Growth phase marks a transition to positive operating cash flows, break-even achievement, and enhanced profitability, enabling access to long-term debt instruments ([Dickinson, 2011](#)).

The Maturity phase represents the pinnacle of operational profit and cash flow generation, alongside negative investment and financial cash flows. Firms at this stage prioritise internal financing, minimise corporate risk, and distribute significant dividends. Mature companies exhibit cash flows that exceed profit and show minimal changes in working capital accruals due to limited investment in current assets ([Damodaran, 2018](#)). In the Shake-out phase, profitability declines and market consolidation occurs, often accompanied by ambiguous cash flow patterns. Firms may either seek to rejuvenate their life cycle through investment or curtail operations. Cash flow patterns in this phase often become ambiguous, reflecting the uncertainty of the firm's direction ([Dickinson, 2011](#)). The Decline stage is typified by diminishing sales, profits, and cash flows, with firms focusing on debt reduction and asset liquidation to meet creditor obligations ([Dvorsky et al., 2022](#)).

Financial distress is a critical area of study in corporate finance, as it serves as a precursor to insolvency and bankruptcy. [Beaver \(1966\)](#) was among the pioneers in exploring financial distress, outlining its various manifestations, including bankruptcy, unsecured bonds, bank overdrafts, and non-payment of preferred share dividends. [Fitzpatrick \(1932\)](#) characterised financial distress as a firm's inability to meet its financial obligations upon maturity. Expanding on this concept, [Purnanandam \(2008\)](#) presented financial distress as a transitional state between solvency and insolvency, offering a theoretical model for risk management. [Opler and Titman \(1994\)](#) further highlighted the disruption financial distress causes in the relationships with creditors and non-financial stakeholders, raising associated costs and limiting access to fresh capital. [Pindado and Rodrigues \(2004\)](#) distinguished between financial distress and insolvency, noting that, while insolvency and bankruptcy presuppose financial distress, a firm can be in distress without reaching insolvency. Their work emphasised the dual legal and strategic dimensions of bankruptcy.

[Platt and Platt \(2006\)](#) delineated the distinction between bankruptcy and financial distress, arguing that bankruptcy often represents a strategic decision to safeguard assets from creditors, whereas financial distress arises from operational inefficiencies or external pressures. They identified markers of distress, such as sustained negative net operating income, dividend suspensions, financial restructuring, and substantial layoffs. [Grice and Dugan \(2003\)](#) corroborated these findings, asserting that, while financial distress precedes all bankruptcies, not all distress culminates in bankruptcy. [A. Akbar et al. \(2019\)](#) identified a U-shaped relationship between life cycle stages and bankruptcy risk, with start-ups and firms in decline facing the highest risks. Later, [M. Akbar et al. \(2022\)](#) examined corporate restructuring, demonstrating that the restructuring approach adopted correlates with the firm's life cycle stage.

[Gopalakrishnan and Mohapatra \(2020\)](#) provided evidence that robust insolvency frameworks reduce default risks, particularly during periods of economic uncertainty.

Closset et al. (2023) explored insolvency law reforms across 15 European nations, finding that, while these reforms fostered restructuring, they also heightened the cost of debt, especially for firms nearing default. Voda et al. (2021) developed a predictive model for bankruptcy risks among Romanian firms in the manufacturing and extractive industries, identifying debt-to-asset ratio, short-term debt ratio, and return on assets as pivotal indicators of distress. Modina and Zedda (2023) similarly highlighted factors such as elevated indebtedness, low capitalisation, and inadequate inventory management as indicators of insolvency. Radovanovic and Haas (2023), on the other hand, integrated bankruptcy prediction with the issue of socio-economic costs, such as the costs associated with job loss. By employing methods such as logistic regression, multiple discriminant analysis, and machine learning, they found that even minor differences in model performance are linked to substantial socio-economic costs.

Lohmann and Möllenhoff (2023) introduced a bankruptcy risk matrix to enhance traditional prediction models, offering a visualisation of current risks and trends. Similarly, Dokiienko et al. (2024) proposed a three-factor model analysing financial stability, liquidity, and profitability, accompanied by a novel matrix for crisis classification. Gupta et al. (2024) examined the strategic behaviours of U.S. firms nearing bankruptcy, revealing that large firms tend to increase their leverage approximately four years before filing for Chapter 11. Intriguingly, higher leverage often enables these firms to avert bankruptcy more effectively than lower leverage levels.

Ivanova et al. (2024) explored the role of CEOs in influencing financial risk in Swedish firms, associating heightened bankruptcy risk with higher leverage, reduced cash reserves, and increased debt costs. Risk-prone executives were observed to escalate debt levels despite short-term losses. Mehmood and De Luca (2023) introduced an innovative financial metric—cash and cash equivalents to current liabilities—which enhances the accuracy of troubled debt restructuring forecasts compared to traditional ratios like working capital to total assets.

Valaskova et al. (2023) and Papik and Papikova (2023) examined the impact of the COVID-19 pandemic on financial health prediction models. Papik and Papikova (2023) specifically argued that the pandemic substantially impaired these models' performance, necessitating recalibration to account for the economic turbulence during the crisis. Horvathova et al. (2023) explored unconventional predictive methodologies, such as graph theory. Meanwhile, Vukcevic et al. (2024) evaluated traditional models like the Altman Z-score and Zmijewski model, finding limited predictive accuracy in the former. Horvathova et al. (2024) demonstrated that machine-learning methods, including Ada-Boost and Gradient Boosting, outperformed traditional methods like logistic regression in predictive ability. Key predictive factors included return on cost and total debt to total assets in Slovak construction companies.

Letkovsky et al. (2024) highlighted the use of AI for bankruptcy prediction through neural networks, decision trees, and support vector machines. In Slovak chemical companies, these methods achieved over 95% predictive accuracy, with similar results observed in the engineering sector (Letkovsky et al., 2023). Durana and Valaskova (2022) and Korol and Fotiadis (2022) agreed on the increasing relevance of AI in bankruptcy prediction within the Industry 4.0 environment. Additionally, Kliestik et al. (2020) proposed neural networks as effective learning algorithms for this purpose.

Indebtedness consistently emerges as a critical determinant of financial distress. Valaskova et al. (2023) examined sectoral influences on debt policies, while Kliestik et al. (2020) identified the current ratio, total liabilities to total assets, and total sales to total assets as key predictors of financial distress risk. Cluster analysis revealed varying distress indicators across different economies, despite shared economic and political conditions.

Belas et al. (2023) broadened this perspective by exploring the role of country-specific, industry-specific, and demographic factors, such as SME managers' age and gender, in Central European countries. Civelek et al. (2023) found that innovation reduces financial risk among SMEs, although competitiveness showed no significant impact. Blazek et al. (2023) noted that, post-COVID-19, larger firms reverted to ethical practices, while smaller firms relied on creative accounting for survival.

Kitowski et al. (2022) demonstrated that the Altman model's predictive ability is lower in Poland compared to models tailored to local contexts. Conversely, Cavlin et al. (2023) applied the Altman Z-score to Serbia's meat processing industry, identifying ROA and current liquidity as significant predictors. Antonowicz et al. (2023) suggested that financial distress signs appear three years before bankruptcy, advocating for dynamic over static indicators for early-warning systems. Bolek and Gniadkowska-Szymanska (2022) confirmed the effectiveness of the Altman and Gajda-Stos models for Polish listed companies but noted challenges to interpreting the results for firms with aggressive investment strategies. Jaki and Cwiek (2021) recommended integrating market measures to enhance model reliability, while Kapounek et al. (2022) found the Altman model sufficiently reliable for large European companies. Kozel et al. (2022) supported its effectiveness in Czech mining companies. Kljucnikov et al. (2022) analysed bankruptcy risk's effect on V4 companies' export decisions, finding that cultural and tax differences are more perceptible, though export costs remain unaffected.

These findings highlight that a company's financial condition and bankruptcy risk are closely linked to its life cycle stage. Start-ups and firms in decline are most vulnerable to bankruptcy, but financial distress can affect companies at all stages, with varying outcomes and responses. Based on the previous findings, we formulated the following research questions:

1. how does the reliability of different bankruptcy prediction models vary across corporate life cycle stages in Central European SMEs?
2. which financial distress prediction model provides the highest accuracy for specific life cycle stages, such as Introduction, Growth, or Decline?

3. Materials and Methods

As outlined in the Introduction, the objective of this study is to analyse and evaluate the predictive capabilities of selected models within the framework of the corporate life cycle. The stages of a company's life cycle can be defined in various ways, as noted by Gulec and Karacaer (2017). According to Dickinson's (2011) model, distinct combinations of operating, investing, and financing cash flows can effectively differentiate the various stages of a company's life cycle. Eight distinct combinations, as presented in Table 1, correspond to the five stages of the business life cycle.

Table 1. Cash flow patterns of Dickinson (2011) corporate life cycle.

Cash Flow	Introduction	Growth	Maturity	Shake-Out			Decline	
Operating	negative	positive	positive	negative	positive	negative	negative	negative
Investing	negative	negative	negative	negative	positive	positive	positive	positive
Financing	positive	positive	negative	negative	positive	negative	positive	negative

Source: Dickinson (2011).

In this case study, the risk of bankruptcy or financial distress for a company is defined using five bankruptcy prediction models. Models developed through logistic regression and discriminant analysis methods were selected. Both methods have distinct advantages and disadvantages in the context of bankruptcy prediction (Radovanovic & Haas, 2023).

The modified Zmijewski model, as revised by [Grice and Dugan \(2003\)](#), adapts the original [Zmijewski \(1984\)](#) probit model to enhance the prediction of financial distress, utilising an unbalanced sample of financially healthy and financially distressed firms. A company is deemed financially healthy if the probability of bankruptcy risk (financial distress) is below 0.5 (50%).

$$X = -2.654 - 4.076X_1 + 1.921X_2 + 0.991X_3, \quad (1)$$

$$P = \frac{e^X}{1 + e^X} \quad (2)$$

where

$$X_1 = \text{EAT} / \text{Total assets}$$

$$X_2 = \text{Debt} / \text{Total assets}$$

$$X_3 = \text{Current assets} / \text{Current liabilities}$$

The Poznanski model is among the most widely utilised models developed within the context of the Polish economy ([Wieprow & Barlik, 2017](#)). Its construction involved a sample of 100 Polish companies, comprising 50 financially distressed and 50 prosperous firms. The final model, developed using the multiple discriminant analysis (MDA) method, incorporates four financial ratio indicators. It is predominantly applied to industry and demonstrates a notable accuracy rate of 92.98% ([Durica & Zvarikova, 2017](#)). If the value of Z_p is negative, the company faces an elevated risk of financial distress, whereas a higher value indicates financial stability.

$$Z_p = -2.368 + 3.562X_1 + 1.588X_2 + 4.288X_3 + 6.719X_4, \quad (3)$$

where

$$X_1 = \text{EAT} / \text{Total assets}$$

$$X_2 = (\text{Current assets} - \text{Inventory}) / \text{Current liabilities}$$

$$X_3 = (\text{Equity} + \text{long-term debt}) / \text{Total assets}$$

$$X_4 = \text{Profit on sales} / \text{Net revenues on sales}$$

In 2011, Petr Jakubik and Petr Teply developed a LOGIT model based on a sample of 757 businesses, 151 of which were bankrupt ([Jakubik & Teply, 2011](#)). The data employed were drawn from financial statements covering the period from 1993 to 2005, and the resulting model comprises seven indicators. This model is specifically targeted at the non-financial sector and demonstrates an accuracy rate of 80.41%. If the probability value is below 0.5, the company is considered financially stable, whereas a value above 0.5 indicates financial distress.

$$JT = 2.4192 + 2.57779X_1 + 1.7863X_2 - 3.4902X_3 - 2.4172X_4 + 1.7679X_5 - 3.3062X_6 - 2.2491X_7, \quad (4)$$

$$P = \frac{e^{JT}}{1 + e^{JT}} \quad (5)$$

where

$$X_1 = \text{Total liabilities} / \text{Equity}$$

$$X_2 = \text{Long-term debt} / \text{Equity}$$

$$X_3 = \text{EBIT} / \text{Interest paid}$$

$$X_4 = \text{EBIT} / \text{Sales}$$

$$X_5 = \text{Inventory} / \text{Average daily turnover}$$

$$X_6 = \text{Cash} / \text{Current liabilities}$$

$$X_7 = \text{EAT} / \text{Equity}$$

The Virag–Hajdu model was developed in 1996 as part of a set of 41 models that encompass both the entire Hungarian economy and specific industries (Virag & Hajdu, 1996). Among these models, this one demonstrates a notable accuracy rate of 77.90%. It is specifically designed for industrial application and is based on four financial indicators. The development of the model involved the analysis of 154 enterprises, 77 of which were bankrupt. The threshold value for distinguishing between financially stable enterprises and those facing financial distress is set at 2.61612. If a company exceeds this value, it is considered financially stable, whereas falling below it indicates financial distress.

$$Z = 1.3566X_1 - 1.63397X_2 - 3.66384X_3 - 0.03366X_4, \quad (6)$$

where

$X_1 = (\text{Current assets} - \text{Inventory}) / \text{Current liabilities}$

$X_2 = \text{Cash flow} / \text{Total debt}$

$X_3 = \text{Current assets} / \text{Total assets}$

$X_4 = \text{Cash flow} / \text{Total assets}$

The last model analysed was developed by Kliestik et al. (2018) using the logistic regression method for medium-sized enterprises in NACE category C—industry. The model's accuracy, as measured by the AUC, was 0.944, indicating a high level of reliability in predicting financial difficulties. Like other logistic regression models, a value greater than 0.5 indicates an elevated risk of financial distress or bankruptcy.

$$\pi_{sNACE1} = -7.084 + 2.931X_1 + 6.884X_2 + 0.609X_3 + 0.006X_4 + 0.050X_5 - 5.929X_6 - 0.139X_7 - 1.390X_8, \quad (7)$$

$$P = \frac{e^{\pi_{sNACE1}}}{1 + e^{\pi_{sNACE1}}} \quad (8)$$

where

$X_1 = \text{Operating profit} / \text{Total assets}$

$X_2 = \text{Total liabilities} / \text{Total assets}$

$X_3 = \text{Current assets} / \text{Total assets}$

$X_4 = \text{Inventory} / \text{Sales}$

$X_5 = (\text{Current assets} - \text{Inventory}) / \text{Current liabilities}$

$X_6 = \text{EAT} / \text{Total assets}$

$X_7 = \text{EAT} / \text{Equity}$

$X_8 = \text{EBT} / \text{Operating revenue}$

The reliability of each model was evaluated using the confusion matrix and metrics such as the true positive rate (TPR, sensitivity), true-negative rate (TNR, specificity), false-positive rate (FPR, type I error rate), false-negative rate (FNR, type II error rate), and accuracy (ACC). A limitation of these metrics arises from data imbalance, where one class is disproportionately larger than the other, reducing the informational value of the metrics (Luque et al., 2019). Alternative metrics, which are less influenced by class imbalance, tend to provide higher reliability.

Balanced accuracy represents the arithmetic mean of sensitivity and specificity, accounting for correct predictions in both classes when one class is significantly more numerous.

$$\text{balanced ACC} = \frac{\text{TPR} + \text{TNR}}{2}, \quad (9)$$

The *F1* score represents the harmonic mean of recall (sensitivity) and precision, defined as the proportion of true positives to all positively predicted values (true positives and false

positives). It is a suitable metric when both sensitivity and precision need to be optimised simultaneously, particularly in cases of unbalanced data.

$$F1\ score = \frac{2 \times Precision \times Sensitivity}{Precision + Sensitivity}, \quad (10)$$

The $F2$ score is like the $F1$ score but places greater emphasis on sensitivity over precision. It is used in scenarios where correctly identifying positive cases and minimising false negatives are particularly important.

$$F2\ score = \frac{5 \times Precision \times Sensitivity}{4 \times (Precision + Sensitivity)}, \quad (11)$$

The Matthews correlation coefficient (MCC) is a robust metric for evaluating the performance of classification models, including bankruptcy risk prediction models. It considers all four values from the confusion matrix, ensuring that it is not biased towards unbalanced classes. Unlike the $F1$ and $F2$ scores, the MCC is also unaffected by which class is designated as positive.

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}, \quad (12)$$

The higher the reliability of the model, the higher the four metrics mentioned above. Similar to the Pearson correlation coefficient, the MCC assumes a value in the range of -1 to 1 , where 1 indicates that the predictions are completely correct, while -1 represents a situation where all the model's predictions are incorrect. A value of 0 suggests that the model provides random predictions.

A necessary condition for evaluating the model using the confusion matrix is the establishment of criteria to classify the investigated entity as being in either a positive or negative state, both in terms of predicted outcomes and actual conditions. The distinction between financial distress and financial stability is determined by the parameters of the individual prediction models. The actual financial condition of the company is assessed based on the equity-to-debt ratio. If the value of this ratio is below 0.08 , it indicates significant financial difficulties and an increased likelihood of financial distress or bankruptcy. Conversely, a value exceeding this threshold suggests greater financial stability. This threshold is derived from the Slovak Commercial Code. However, due to the economic similarities among Central European countries, it can also serve as a reliable indicator of elevated financial distress risk within this broader regional context (Valaskova et al., 2023).

The data required for the analysis of the models' reliability were sourced from the Orbis database, using four selection criteria: the company's registered office is in one of the Central European countries (the Czech Republic, Hungary, Poland, and Slovakia), assets exceeding EUR $500,000$, inclusion in NACE category C—Manufacturing, and classification as a small or medium-sized enterprise. These criteria ensure the comparability of the companies analysed in the study, as the financial health prediction models under review were developed within the context of Central European countries.

In total, the initial sample comprised 6725 enterprises meeting the specified criteria, with the data corresponding to the year 2022 . The final sample was refined by removing observations with missing data and applying winsorising at the 1% and 99% levels to eliminate extreme values. The total sample was then divided into twenty sub-samples based on two distinguishing variables: country and stage of the life cycle. Each financial health prediction model was analysed within these sub-samples and evaluated according to the criteria.

4. Results and Discussion

In the initial stage of the financial distress risk prediction analysis, the sample was refined by removing entries with missing or extreme values. The resulting net sample comprised 5785 small and medium-sized enterprises (SMEs) in the manufacturing sector from four Central European countries. Figure 1 illustrates the classification of companies based on their equity-to-debt ratio, distinguishing between financially stable firms (with an equity-to-debt ratio greater than 0.08) and financially unstable firms, or those with a higher risk of financial distress (with an equity-to-debt ratio below 0.08).

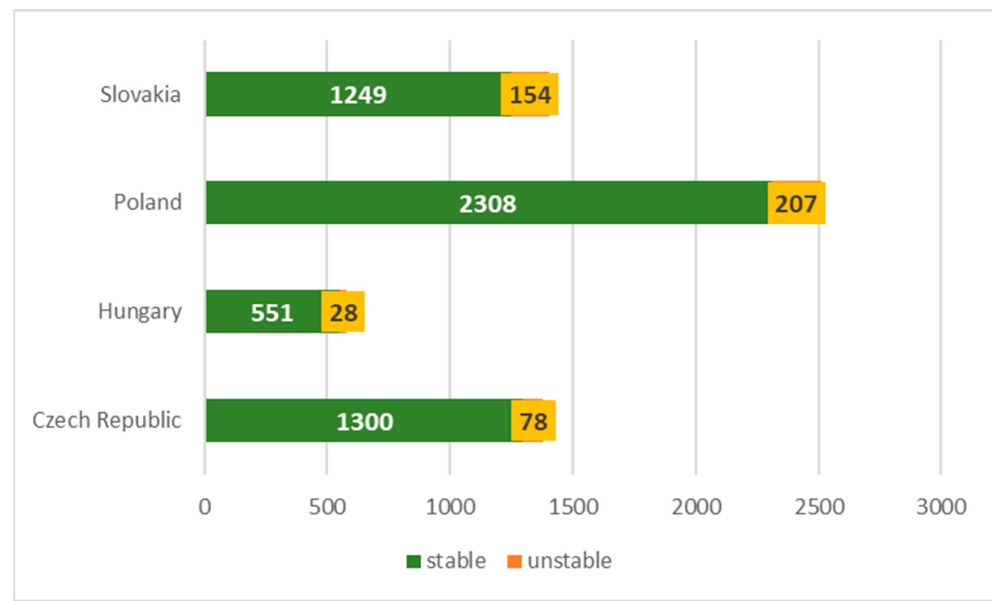


Figure 1. Distribution of the sample according to financial stability of company.

All sub-samples based on the equity-to-debt indicator exhibit significant imbalance, with nearly 90% or more of the companies in each sub-sample classified as financially stable. This imbalance poses challenges to the application of traditional metrics such as sensitivity, specificity, and accuracy. To address these issues, the study employed advanced metrics, such as balanced accuracy, *F1* and *F2* scores, and the Matthews correlation coefficient (*MCC*), which are designed to account for class imbalance and provide a more equitable evaluation of model performance across both positive and negative classes. Figure 2 illustrates the distribution of enterprises according to their stage in the life cycle.

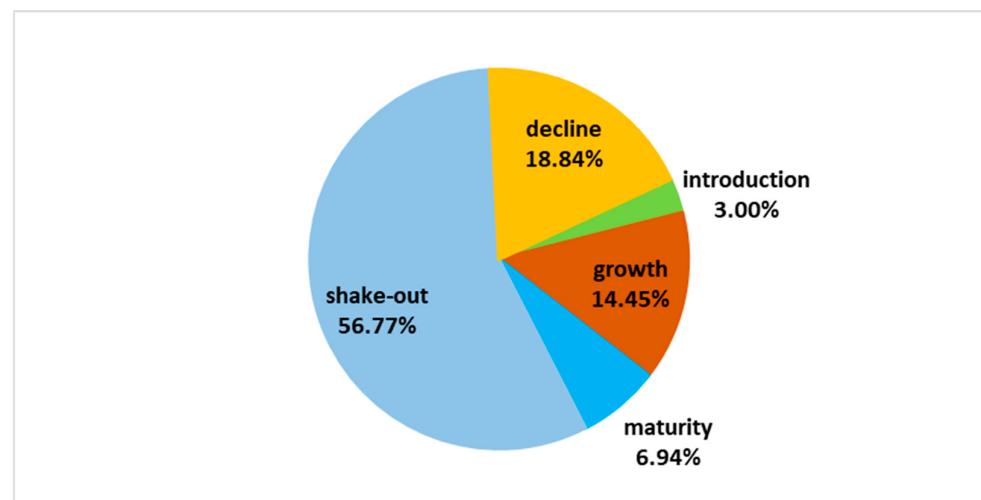


Figure 2. Distribution of the sample according to corporate life cycle stage.

Most companies in the investigated sub-samples are in the shake-out stage, characterised as an indeterminate phase between peak performance and decline. Start-ups and mature enterprises in the stability stage represent the smallest proportion. This distribution of enterprises aligns with their financial stability classification, as growing, mature, and shake-out businesses typically exhibit stable financial performance, often reflected in positive operating cash flow.

Table 2 presents an overview of the descriptive statistics for the investigated models, categorised by the stages of the corporate life cycle. This table provides insights into the distribution and key characteristics of the models' performance across different life cycle stages, enabling a comparative analysis of their predictive abilities during phases such as growth, maturity, and shake-out.

Table 2. Descriptive statistics of risk of financial distress according to the stages of life cycle.

Life Cycle Period	Introduction		Growth		Maturity		Shake-Out		Decline	
Model	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Modified Zmijewski	0.7924	0.2621	0.5778	0.3502	0.5931	0.3682	0.5225	0.3643	0.7475	0.3143
Poznanski	1.6518	6.8309	3.2614	3.6427	0.5871	28.1728	2.3325	64.8130	1.0665	6.2271
Jakubik–Teply	0.8013	0.3990	0.5524	0.4932	0.7525	0.4305	0.6544	0.4724	0.8138	0.3861
Virag–Hajdu	3.9355	2.8935	4.0256	4.6642	3.9889	5.8707	4.9306	5.5627	4.0047	4.7675
Kliestik, et al.	0.2099	0.2381	0.0861	0.1276	0.1475	0.2358	0.0978	0.1791	0.2530	0.3118

The average values of financial distress risk, expressed as the probability of financial distress (according to the modified Zmijewski, Jakubik–Teply, and Kliestik et al. models), exhibit a U-shaped pattern. Start-up and declining businesses generally face a higher average risk of financial distress, whereas mature businesses tend to experience a lower risk.

In contrast, the discriminant analysis models, specifically the Poznanski and Virag–Hajdu models, yield less definitive results on average; neither model clearly distinguishes between the stages of the life cycle in terms of financial distress risk. However, both models display a notably high standard deviation, indicating significant variability in the descriptive statistics results.

Overall, the results of the models suggest a certain influence of the company's life cycle on the prediction of financial distress risk. The study provides a rigorous analysis of the predictive capabilities of various models across the stages of the corporate life cycle. The accuracy and reliability of the models were evaluated using robust metrics, including balanced accuracy, *F1* and *F2* scores, and the Matthews correlation coefficient (*MCC*), which account for class imbalance and offer a nuanced assessment of model performance. By systematically comparing predicted outcomes with the actual financial conditions of companies, the research highlights the varying reliability of these models, with particular emphasis on their strengths and limitations at different stages of the corporate life cycle. Table 3 presents the results of various performance metrics, including the true-positive rate (*TPR*), true-negative rate (*TNR*), false-positive rate (*FPR*), false-negative rate (*FNR*), accuracy (*ACC*), balanced accuracy (*bal ACC*), *F1* and *F2* scores, and Matthews correlation coefficient (*MCC*) for the modified Zmijewski model by [Grice and Dugan \(2003\)](#).

Table 3. Reliability of the modified Zmijewski model in the country–life cycle subsamples.

Model		Modified Zmijewski								
Country	Life Cycle	TPR	TNR	FNR	FPR	ACC	bal ACC	F1	F2	MCC
Czech Republic	Introduction	0.140	1.000	0.860	0.000	0.204	0.570	0.246	0.169	0.109
	Growth	0.543	0.889	0.457	0.111	0.557	0.716	0.702	0.597	0.192
	Maturity	0.500	0.857	0.500	0.143	0.524	0.679	0.662	0.554	0.216
	Shake-out	0.550	1.000	0.450	0.000	0.567	0.775	0.710	0.605	0.210
	Decline	0.352	1.000	0.648	0.000	0.440	0.676	0.521	0.404	0.262
Hungary	Introduction	0.111	1.000	0.889	0.000	0.273	0.556	0.200	0.135	0.135
	Growth	0.454	1.000	0.546	0.000	0.459	0.727	0.624	0.509	0.092
	Maturity	0.392	1.000	0.608	0.000	0.426	0.696	0.563	0.446	0.186
	Shake-Out	0.591	1.000	0.409	0.000	0.600	0.796	0.743	0.644	0.173
	Decline	0.197	1.000	0.803	0.000	0.337	0.599	0.329	0.235	0.203
Poland	Introduction	0.245	1.000	0.755	0.000	0.375	0.623	0.394	0.289	0.230
	Growth	0.482	1.000	0.518	0.000	0.493	0.741	0.650	0.538	0.139
	Maturity	0.528	1.000	0.472	0.000	0.562	0.764	0.691	0.583	0.273
	Shake-Out	0.550	0.985	0.450	0.015	0.571	0.768	0.709	0.604	0.230
	Decline	0.309	1.000	0.691	0.000	0.442	0.655	0.472	0.359	0.281
Slovakia	Introduction	0.098	1.000	0.902	0.000	0.213	0.549	0.178	0.119	0.117
	Growth	0.260	1.000	0.740	0.000	0.298	0.630	0.412	0.305	0.134
	Maturity	0.276	1.000	0.724	0.000	0.357	0.638	0.432	0.323	0.203
	Shake-Out	0.378	1.000	0.622	0.000	0.441	0.689	0.549	0.432	0.241
	Decline	0.183	1.000	0.817	0.000	0.342	0.592	0.310	0.219	0.204

The TPR, TNR, FNR, and FPR indicators reveal an imbalance in the data across individual sub-samples, with the TNR value (specificity) reaching a maximum, while the FPR value is minimal. This is attributable to the extreme data imbalance. The number of true negatives in the sub-samples was very low, and the number of false positives was also very low or zero. In this analysis, a high risk of financial distress was considered a negative state, and vice versa. However, the model produced numerous false-negative predictions, indicating a higher risk of financial distress than the companies faced. As a result, the accuracy (ACC) of the model is significantly distorted and deviates from the balanced accuracy (bal ACC), which provides a more accurate depiction of the model's reliability as it equally weights sensitivity and specificity, making it particularly suitable for imbalanced datasets.

The models performed better in the maturity and shake-out stages, achieving a higher rate of correct predictions (i.e., true positives and true negatives). In these stages, the *balanced ACC* ranges at 0.6 and above, indicating that the modified Zmijewski model correctly identifies at least 60% of mature and shake-out enterprises that face an elevated risk of financial distress.

The Poznanski model also exhibits class imbalance, as indicated by the differing values of ACC and *balanced ACC* in Table 4. The *balanced ACC* reaches lower values in the Introduction stage within the Czech sub-sample, whereas in other countries, it achieves relatively high values, particularly in terms of both the *F1* and *F2* scores. The *MCC*, regarded as the most robust metric, also underscores the model's higher reliability in the Introduction stage for Hungarian, Polish, and Slovak sub-samples, as well as its strong performance in predicting the risk of financial distress for declining companies. Overall, the model demonstrates relatively good predictive ability across the various stages of the life cycle.

The third model (Table 5), like the modified Zmijewski model, suffers from class imbalance, as evidenced by the high TNR value and, conversely, the low FPR value. The Jakubik–Teply model exhibits a significantly higher frequency of false negatives (FN) and a correspondingly low frequency of true negatives (TN) and false positives (FP). The most

prevalent class is true positive (TP), regardless of the country or life cycle stage. A notable advantage of this model is its very low frequency of false positives, meaning it rarely misclassifies companies as financially stable when they are, in fact, in distress.

Table 4. Reliability of the Poznanski model in the country–life cycle subsamples.

Model		Poznanski								
Country	Life Cycle	TPR	TNR	FNR	FPR	ACC	bal ACC	F1	F2	MCC
Czech Republic	Introduction	0.900	0.250	0.100	0.750	0.852	0.575	0.918	0.907	0.188
	Growth	0.962	0.444	0.038	0.556	0.941	0.703	0.969	0.965	0.373
	Maturity	0.823	0.857	0.177	0.143	0.825	0.840	0.898	0.851	0.426
	Shake-out	0.920	0.500	0.080	0.500	0.904	0.710	0.949	0.931	0.298
	Decline	0.827	0.786	0.173	0.214	0.821	0.806	0.889	0.851	0.509
Hungary	Introduction	0.889	1.000	0.111	0.000	0.909	0.944	0.941	0.909	0.770
	Growth	0.959	1.000	0.041	0.000	0.959	0.979	0.979	0.967	0.438
	Maturity	0.843	1.000	0.157	0.000	0.852	0.922	0.915	0.870	0.480
	Shake-Out	0.941	0.714	0.059	0.286	0.936	0.828	0.967	0.951	0.373
	Decline	0.789	0.800	0.211	0.200	0.791	0.794	0.862	0.816	0.516
Poland	Introduction	0.868	0.364	0.132	0.636	0.781	0.616	0.868	0.868	0.316
	Growth	0.975	0.667	0.025	0.333	0.968	0.821	0.984	0.978	0.484
	Maturity	0.908	0.909	0.092	0.091	0.908	0.909	0.949	0.924	0.597
	Shake-Out	0.944	0.603	0.056	0.397	0.928	0.774	0.962	0.951	0.442
	Decline	0.826	0.748	0.174	0.252	0.811	0.787	0.876	0.845	0.540
Slovakia	Introduction	0.854	0.667	0.146	0.333	0.830	0.760	0.897	0.871	0.464
	Growth	0.881	0.615	0.119	0.385	0.867	0.748	0.926	0.898	0.343
	Maturity	0.713	0.909	0.287	0.091	0.735	0.811	0.827	0.754	0.427
	Shake-Out	0.817	0.718	0.183	0.282	0.807	0.768	0.884	0.843	0.416
	Decline	0.754	0.804	0.246	0.196	0.764	0.779	0.837	0.785	0.501

Table 5. Reliability of the Jakubik–Teply model in the country–life cycle subsamples.

Model		Jakubik–Teply								
Country	Life Cycle	TPR	TNR	FNR	FPR	ACC	bal ACC	F1	F2	MCC
Czech Republic	Introduction	0.140	1.000	0.860	0.000	0.204	0.570	0.246	0.169	0.109
	Growth	0.476	0.667	0.524	0.333	0.484	0.571	0.639	0.530	0.126
	Maturity	0.219	0.857	0.781	0.143	0.262	0.538	0.356	0.259	0.115
	Shake-out	0.318	0.933	0.682	0.067	0.341	0.625	0.481	0.368	0.122
	Decline	0.173	0.821	0.827	0.179	0.261	0.497	0.288	0.206	0.128
Hungary	Introduction	0.222	1.000	0.778	0.000	0.364	0.611	0.364	0.263	0.222
	Growth	0.526	1.000	0.474	0.000	0.531	0.763	0.689	0.581	0.106
	Maturity	0.196	1.000	0.804	0.000	0.241	0.598	0.328	0.234	0.116
	Shake-Out	0.372	1.000	0.628	0.000	0.385	0.686	0.542	0.425	0.111
	Decline	0.155	1.000	0.845	0.000	0.302	0.577	0.268	0.186	0.176
Poland	Introduction	0.283	0.909	0.717	0.091	0.391	0.596	0.435	0.329	0.224
	Growth	0.475	0.833	0.525	0.167	0.482	0.654	0.642	0.530	0.114
	Maturity	0.408	1.000	0.592	0.000	0.451	0.704	0.580	0.463	0.217
	Shake-Out	0.388	0.868	0.612	0.132	0.411	0.628	0.556	0.441	0.148
	Decline	0.219	0.865	0.781	0.135	0.343	0.542	0.350	0.257	0.186
Slovakia	Introduction	0.220	0.833	0.780	0.167	0.298	0.526	0.353	0.259	0.149
	Growth	0.396	0.923	0.604	0.077	0.423	0.659	0.565	0.450	0.168
	Maturity	0.126	1.000	0.874	0.000	0.224	0.563	0.224	0.153	0.126
	Shake-Out	0.338	0.872	0.662	0.128	0.392	0.605	0.500	0.388	0.191
	Decline	0.183	0.891	0.817	0.109	0.321	0.537	0.303	0.218	0.172

However, despite this, the model demonstrates low overall reliability across all life cycle stages and countries, as indicated by the Matthews correlation coefficient (MCC). The

MCC values across all of the investigated sub-samples are below 0.22, suggesting that the model's predictive performance is close to random chance.

The Hungarian Virag–Hajdu model (Table 6.), like the modified Zmijewski and Jakubik–Teply models, is characterised by a lower MCC value. Among the studied models, it has the lowest average MCC, regardless of country affiliation, except in the Decline stage. In this stage, the model demonstrates improved performance across all metrics.

Table 6. Reliability of the Virag–Hajdu model in the country–life cycle subsamples.

Model		Virag–Hajdu								
Country	Life Cycle	TPR	TNR	FNR	FPR	ACC	bal ACC	F1	F2	MCC
Czech Republic	Introduction	0.840	0.000	0.160	1.000	0.778	0.420	0.875	0.854	0.000
	Growth	0.833	0.333	0.167	0.667	0.813	0.583	0.895	0.857	0.146
	Maturity	0.844	0.429	0.156	0.571	0.816	0.636	0.895	0.864	0.240
	Shake-out	0.848	0.300	0.152	0.700	0.828	0.574	0.905	0.870	0.133
	Decline	0.799	0.536	0.201	0.464	0.763	0.667	0.854	0.820	0.340
Hungary	Introduction	0.556	0.500	0.444	0.500	0.545	0.528	0.667	0.595	0.215
	Growth	0.680	0.000	0.320	1.000	0.673	0.340	0.805	0.725	0.000
	Maturity	0.549	0.333	0.451	0.667	0.537	0.441	0.691	0.598	0.084
	Shake-Out	0.771	0.571	0.229	0.429	0.767	0.671	0.866	0.806	0.149
	Decline	0.577	0.667	0.423	0.333	0.593	0.622	0.701	0.621	0.293
Poland	Introduction	0.792	0.364	0.208	0.636	0.719	0.578	0.824	0.805	0.257
	Growth	0.766	0.500	0.234	0.500	0.761	0.633	0.862	0.802	0.129
	Maturity	0.796	0.545	0.204	0.455	0.778	0.671	0.869	0.824	0.267
	Shake-Out	0.824	0.485	0.176	0.515	0.808	0.655	0.891	0.850	0.216
	Decline	0.747	0.514	0.253	0.486	0.702	0.630	0.802	0.768	0.329
Slovakia	Introduction	0.683	0.167	0.317	0.833	0.617	0.425	0.757	0.711	0.083
	Growth	0.609	0.692	0.391	0.308	0.613	0.650	0.749	0.658	0.191
	Maturity	0.632	0.545	0.368	0.455	0.622	0.589	0.748	0.674	0.223
	Shake-Out	0.711	0.474	0.289	0.526	0.687	0.593	0.803	0.745	0.220
	Decline	0.738	0.587	0.262	0.413	0.709	0.663	0.803	0.763	0.366

Like the previous models, the Virag–Hajdu model struggles with a high frequency of false-negative predictions. However, in the Decline stage, it more effectively identifies companies in financial distress compared to other stages. This stage of the life cycle is inherently associated with a higher risk of financial distress, making the accurate detection of impending financial difficulties particularly valuable, as it enables the implementation of appropriate safety measures for at-risk enterprises.

The model developed by Klietnik et al. for Slovak companies demonstrates exceptional reliability, with all relevant metrics achieving notably strong values, as shown in Table 7. Analysis of the confusion matrix reveals minimal occurrences of false negatives and false positives, ensuring that the model consistently identifies either financial stability or heightened financial distress with precision.

While the model's performance is slightly diminished in the Czech sub-sample compared to other countries, it still outperforms the alternative models across all country sub-samples. When analysed through the lens of the corporate life cycle, its reliability exhibits some variation. The model achieves highly balanced accuracy during the Introduction and Decline stages, effectively identifying companies at financial risk. However, during the Growth stage, particularly in the Czech, Polish, and Slovak sub-samples, companies in financial distress are less frequently classified as risky. This results in a higher rate of false positives, where risky enterprises are incorrectly labelled as financially stable.

Table 7. Reliability of the Kliestik, et al. model in the country–life cycle subsamples.

Model		Kliestik, et al.								
Country	Life Cycle	TPR	TNR	FNR	FPR	ACC	bal ACC	F1	F2	MCC
Czech Republic	Introduction	0.980	0.500	0.020	0.500	0.944	0.740	0.970	0.976	0.560
	Growth	1.000	0.444	0.000	0.556	0.977	0.722	0.988	0.995	0.659
	Maturity	0.979	0.714	0.021	0.286	0.961	0.847	0.979	0.979	0.699
	Shake-out	0.990	0.667	0.010	0.333	0.977	0.828	0.988	0.989	0.682
	Decline	0.983	0.857	0.017	0.143	0.966	0.920	0.981	0.982	0.856
Hungary	Introduction	1.000	1.000	0.000	0.000	1.000	1.000	1.000	1.000	1.000
	Growth	1.000	1.000	0.000	0.000	1.000	1.000	1.000	1.000	1.000
	Mature	0.980	1.000	0.020	0.000	0.981	0.990	0.990	0.984	0.857
	Shake-Out	0.988	0.857	0.012	0.143	0.985	0.922	0.992	0.989	0.712
	Decline	0.944	0.800	0.056	0.200	0.919	0.872	0.950	0.946	0.736
Poland	Introduction	0.981	0.727	0.019	0.273	0.938	0.854	0.963	0.974	0.774
	Growth	0.996	0.500	0.004	0.500	0.986	0.748	0.993	0.995	0.608
	Mature	0.986	1.000	0.014	0.000	0.987	0.993	0.993	0.989	0.913
	Shake-Out	0.996	0.662	0.004	0.338	0.981	0.829	0.990	0.994	0.764
	Decline	0.968	0.865	0.032	0.135	0.948	0.916	0.968	0.968	0.837
Slovakia	Introduction	0.951	1.000	0.049	0.000	0.957	0.976	0.975	0.961	0.845
	Growth	0.996	0.462	0.004	0.538	0.968	0.729	0.983	0.991	0.618
	Mature	0.954	0.636	0.046	0.364	0.918	0.795	0.954	0.954	0.607
	Shake-Out	0.988	0.667	0.012	0.333	0.956	0.828	0.976	0.983	0.742
	Decline	0.958	0.870	0.042	0.130	0.941	0.914	0.963	0.960	0.820

Among the models analysed, the Kliestik et al. model emerges as the most reliable across all life cycle stages. The Poznanski model ranks second, exhibiting slightly lower performance. Conversely, the Jakubik–Teply and modified Zmijewski models receive weaker evaluations. The modified Zmijewski model demonstrates more satisfactory performance primarily for mature and shake-out companies, rendering it more appropriate for those stages of the life cycle. Both models, however, struggle with data imbalance, as indicated by their lower MCC scores. The Virag–Hajdu model produces the most inconsistent results, with the reliability varying widely across life cycle stages, raising concerns about its applicability in predicting financial distress regardless of geographic context. Table 8 presents a summary of the advantages and limitations of the analysed models, based on the study’s findings.

Table 8. The strengths and weaknesses of the analysed models.

Model	Strengths	Weaknesses
Kliestik et al.	+ Highest reliability across all life cycle stages.	– Slightly lower accuracy in the Growth stage due to false positives.
Poznanski	+ High sensitivity (TPR), performs well in advanced stages (Maturity, Decline).	– Variable reliability in early stages (Introduction), lower specificity.
Modified Zmijewski	+ Better accuracy in advanced stages (Maturity, Shake-out).	– Poor performance in early stages (Introduction) due to high false-negative rates.
Virag–Hajdu	+ Improved performance in the Decline stage, identifies at-risk companies effectively.	– Inconsistent results across stages, low accuracy in earlier stages.
Jakubik–Teply	+ Low number of false positives.	– Low reliability across all stages, particularly high number of false negatives.

Logistic regression models are strongly endorsed by Kovacova et al. (2018), who, in their comparative study of multiple regression, discriminant analysis, logistic regression, and probit regression, concluded that logistic regression provides the highest predictive

accuracy. However, they noted that discriminant analysis suffers from significant type I and type II errors, a limitation also observed in several models under review. [Kubenka et al. \(2021\)](#) assessed the influence of uncertainty on predictive accuracy and determined that the [Kliestik et al. \(2018\)](#) model, developed on similar principles as the investigated one, retains a predictive accuracy exceeding 85%, particularly excelling in bankruptcy prediction.

The reliability of all of the models is influenced by the life cycle stage of the company. This variability is particularly evident in the modified Zmijewski, Poznanski, and Virag–Hajdu models, which demonstrate higher reliability during the Decline stage. The Jakubik–Teply and Kliestik et al. models, by contrast, exhibit consistent reliability across all stages. [M. Akbar et al. \(2022, 2021, 2020\)](#) also highlight the relationship between bankruptcy probability and life cycle stages, identifying the Decline stage as critical, where declining profitability serves as a key indicator of financial difficulties. Similarly, [Valackiene and Virbickaite \(2011\)](#) emphasise the Decline stage as the most precarious, corroborating findings that models perform better during this stage due to pronounced signs of financial distress.

Two important points warrant further consideration. First, the results of the analysed models are influenced by data imbalance, particularly the high proportion of financially stable enterprises, which affects the choice of evaluation metrics such as the MCC. The MCC is known for its robustness against class imbalance between bankrupt and non-bankrupt enterprises. [Noh \(2023\)](#) advocates for approximate entropy sampling as a method to enhance predictive accuracy across various approaches, including logistic regression. Similarly, [Stankova and Hampel \(2023\)](#) stress the importance of threshold optimisation, noting that traditional models frequently exhibit high type II error rates. They recommend employing the Youden Index to better balance sensitivity and specificity.

Second, the reliability of the models is sensitive to the presence of outliers in the dataset. [Svabova and Durica \(2019\)](#) observed that, in Slovak enterprise samples, nearly 40% of outliers were classified as non-prosperous. They propose incorporating outliers into bankruptcy models rather than excluding them. [Szanto \(2023\)](#) concurs, suggesting that replacing outliers is preferable to removing them. In this study, the winsorisation method was employed, which retains the sample size by replacing outliers rather than excluding them entirely, thereby ensuring a more comprehensive analysis.

5. Conclusions

The global economy has been affected by numerous adverse events in recent years. These challenges have compelled companies to rigorously monitor both external indicators of an impending economic crisis and internal signals of financial distress. Nonetheless, the accuracy of financial distress prediction systems remains a subject of debate, particularly considering the varying conditions present during different stages of the business life cycle.

This study underscores the pivotal importance of understanding the interplay between a firm's life cycle stages and the reliability of bankruptcy prediction models, with specific attention to the context of Central European economics. Using a sample of over 5000 small and medium-sized enterprises, significant variability was identified in the accuracy of financial distress predictions across the life cycle stages, with profound implications for strategic decision-making regarding business continuity. The findings indicate that, while certain models, such as the Kliestik et al. framework, demonstrate consistently high predictive reliability across all life cycle stages, others, including the modified Zmijewski and Virag–Hajdu models, exhibit significant variability that is contingent upon the stage. This variability underscores the critical need for customised approaches to financial health assessment, particularly for firms in precarious stages such as Decline or Growth.

The study also highlights a key dimension of predictive model application: data skewness. Advanced evaluation metrics, such as *F1* and *F2* scores or the Matthews correlation coefficient (*MCC*), proved to be effective in mitigating the biases inherent in traditional metrics. Moreover, integrating the business life cycle into predictive models revealed reduced reliability of outcomes at specific stages, a finding that is especially pertinent in the phases marked by elevated financial distress.

Overall, this research advances the understanding of bankruptcy prediction by linking financial distress with corporate life cycle stages. Companies in the Introduction and Decline stages are at significantly higher risk of financial distress, necessitating targeted support mechanisms during these phases. The U-shaped pattern of risk highlights the need for policies tailored to the specific financial characteristics of each stage. It provides actionable insights for stakeholders, including policymakers, financial analysts, and business managers, enabling improvements in early-detection and intervention strategies, like establishing stage-specific financial aid programs (providing access to affordable credit and venture capital to mitigate liquidity constraints in the Introduction stage or focusing on restructuring loans and incentivising turnaround strategies to avoid bankruptcies in decline stage). Second, the results highlight the need to implement robust prediction models, such as those proposed by Klietk et al., that can be integrated with machine-learning techniques into early-warning systems for SMEs.

Future research should prioritise the incorporation of dynamic indicators and the utilisation of advanced machine-learning techniques to further refine these models and adapt them to the ever-evolving economic landscape.

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