Acta Montanistica Slovaca
ISSN 1335-1788
actamont.tuke.sk

Predicting impending bankruptcy and financial distress of a mining company using the HGN model

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Funding information:
This research was funded by MŠVVaŠ SR Grant Number VEGA 1/0359/23 Implementation of the current relevant determinants of the company's financial performance into the system for early indication of the threat of bankruptcy

How to cite this article:
Hyránek, E. and Mišota, B. (2024). Predicting impending bankruptcy and financial distress of a mining company using the HGN model**,** *Acta Montanistica Slovaca,* Volume 29 (4), 804-818

DOI:
https://doi.org/10.46544/AMS.v29i4.03

Abstract

Early identification of imminent bankruptcy is crucial for saving a company. It allows for timely implementation of essential measures through preventive restructuring. This paper addresses the current issue of identifying impending bankruptcy in non-financial companies. Existing predictive models can be used to detect imminent bankruptcy, but most of them fail to identify it in time. In this paper, we apply our own predictive model, HGN. Previous research has confirmed its usefulness in performance evaluation, as well as its predictive capability. The model takes into account significant factors that influence the unfavourable financial situation of a company.

Detecting the imminent bankruptcy of a company in a timely manner requires an exact approach to modifying the model. The modified version of the model places a strong emphasis on the company's debt situation, regardless of the time horizon of the debt. For the purposes of early identification of impending bankruptcy, the model is tested based on real data from a company in the Mining of chemical and fertiliser minerals sector (SK NACE 08.91.0). The company underwent restructuring and eventually went bankrupt, meeting the criteria for testing the identification of imminent bankruptcy. By substituting certain financial indicators contained in the basic version of the HGN model, we modify its calculation to provide a more objective forecast of undesirable development. The modification emphasises the financial situation and the factors that significantly influence future trends. Based on the comparative analysis and quantified results, we recommend the preference of the HGN model for the early warning system.

Keywords

Early warning system, predictive models, impending bankruptcy, HGN model, preventive restructuring, corporate financial distress

Introduction

At both the national and European levels, legislative frameworks are being adopted to predict the financial difficulties of companies and thus prevent their bankruptcy (AriasVarona et al., 2020; Kokorin, 2021; McCarthy et al., 2020) and maintain their financial stability (Tahotný et al., 2024). This type of legislation is focused on protecting vulnerable creditors of companies, the banking sector, and, not least, the companies themselves (Garrido et al., 2021). The mining industry is one of the sectors with high capital intensity, where economic cycles, changes in demand for its products, and fluctuations in stock market prices are particularly pronounced (Dou et al., 2024; Gradzewicz & Mućk., 2024; Syamni et al., 2018; Valacchi et al., 2023). Therefore, it is even more important to monitor the economic development of mining companies and their performance indicators in mining processes in the context of strategic innovations for sustainable development in this industrial sector (Ludbrook et al., 2019; Teplická et al., 2021), ensuring long-term profitability (Papcunová et al., 2024), resilience and competitiveness in a rapidly evolving global economy (Ejdys et al. 2019).

As mentioned above, the role of strategic innovations including technological innovations is highly crucial for financial sustainability of firms (Alsharif et al., 2024) due to playing a significant role in risk management (Kuděj et al., 2023). Those innovations also make positive contributions on firms' digital transformation (Civelek et al., 2023a) or digitalization process (Bilan et al., 2024) that has a strong relationship with sustainability (Khatami et al., 2024). When firms integrate innovative and sustainable practices in their financial management process such as fintech (Batizani, 2024) and digital financial services (Ngware, 2024), they can also stimulate their economic sustainability (Poliakova et al., 2024).

However, bankruptcy issue has been one of the biggest problems of firms in their survival (Civelek et al., 2023b). This is because especially small firms have a fragile structure that causes financial failures (Civelek et al., 2024; Gavurova et al. 2020). In this regard, bankruptcy prevention in the mining and quarrying sector is becoming increasingly important in the search for answers to the question of how to predict financial difficulties and protect companies in this sector from imminent bankruptcy.

The issue of financial prediction and bankruptcy prevention represents a current, highly dynamic, and complex research area with an interdisciplinary character. Beaver (1966) developed the methodology of univariate analysis of financial indicators. Altman (1968) laid the foundations of modern financial failure prediction theory with his pioneering work on the Z-score, which initiated a systematic scientific approach to identifying risky companies (Hyránek, 2012). Further research, such as Springate (1978), which supplemented and expanded Altman's (1968) work, included many methodological innovations, such as appropriate estimation techniques by Zmijewski (1984), while Ohlson (1980) implemented logistic regression analysis. Mitigating the limitations of individual models led to the development of more sophisticated approaches.

Current research worldwide, including in Slovakia, is characterised by several key trends. Primarily, there is a trend towards a more pronounced shift from static models to dynamic, adaptive models that should be capable of reflecting the turbulence of the business environment. For example, Shumway (2001) proposed a dynamic hazard analysis model that takes into account time-varying risk factors. The use of a dynamic approach has increased the predictive capability of decision trees in predictive models (Gavurova et al., 2017).

The importance of machine learning and artificial intelligence in predictive models is also increasing. Neural networks, statistical methods, and machine learning algorithms offer unprecedented capabilities in identifying complex relationships between financial indicators (Atiya, 2001; Kumar & Ravi, 2007; Wilson & Sharda, 1994; Zhang et al., 2022). These technologies enable the processing of multidimensional datasets with greater accuracy.

Research in the field of financial prediction, or bankruptcy prevention, increasingly emphasises the contextual dependency of predictive models. For this reason, the adaptability of the proposed models to various characteristics, such as sectoral, industry, and regional economic specifics within the economy, is becoming more important (Gavurova et al. 2016). Additionally, there is a significant improvement in prediction through monthly observation intervals (Chava & Jarrow, 2004).

An important challenge remains the integration of financial and non-financial indicators. Empirical studies have clearly demonstrated that financial failure results from a complex interaction of economic, managerial, institutional, and external factors (Tkacova and Gavurova, 2023; Altman et al., 2019).

Systematic meta-analyses highlight the limitations of existing approaches. The significant variability in the accuracy of predictive models indicates the necessity for further methodological research (Balcaen & Ooghe, 2006).

This paper focuses on testing our own model in the context of a mining business. Models used for predicting bankruptcy and assessing the financial health of companies have gradually evolved from classic approaches, such as Altman's Z-score (Altman, 1968), to new innovative methodologies that consider a broader context (Altman et al., 2019; Taffler & Tisshaw, 1977). These state-of-the-art methodologies and research in model application should also take into account industry-specific characteristics, such as the cyclical and capital-intensive nature of the mining industry (Kozel et al., 2022; Syamni et al., 2018). Mining companies face specific risks (Kazakova et al., 2018) arising from commodity price volatility, stock fluctuations (Syamni et al., 2018), and high initial costs. Due to the frequent use of current loans to finance operations, the literature presents approaches using a wide range of indicators to assess the probability of financial distress, which can be used to evaluate creditworthiness through financial statement analysis (Beaver et al., 2011). Despite their wide applicability, traditional models for predicting bankruptcy and assessing financial health do not take into account the specifics of current liabilities and liquidity risks that often arise in the mining sector. When applying traditional models like the Z-score or Taffler's model to the mining industry, it became apparent that they fail to consider cash flow volatility and specific debt associated with current liabilities. Many studies suggest that ignoring these short-term aspects can lead to inaccurate bankruptcy predictions (Altman et al., 2019). The low accuracy of predictions in mining companies has created a need for models that combine short-term and long-term debt indicators, while also considering commodity price volatility and regulatory challenges.

Taking into account short-term debt indicators was one of the motivations for exploring options to predict an unfavourable financial situation. This research expands upon previous work by modifying the HGN model (Hyránek et al., 2021; Hyránek et al., 2018; Hyránek et al., 2017; Hyránek et al., 2014) to adapt it to the mining sector, with a focus on indicators such as current liabilities, cash flow, and the specifics of the regulatory environment. This approach enhances the predictive capability of the HGN model and provides opportunities for more effective monitoring of the financial health of companies in the mining industry.

Material and Methods

The aim of this paper is to explore possibilities for early warning signals of impending bankruptcy through the application of the HGN predictive model. The HGN model, as a financial performance model with predictive capabilities, primarily focuses on the company's debt situation as a common cause of financial failure leading to bankruptcy. An additional goal is to create alternative versions of the model, taking into account specific conditions.

The description of the basic model is provided in the paper *Verification of the Performance Model in Selected Companies in the Mining Industry* by Hyránek et al. in issue 3/2021 of Acta Montanistica Slovaca (Hyránek et al., 2021). Therefore, in this paper, we present a brief summary of the basic version.

The key indicators included in the initial HGN model are as follows:

The efficiency indicators x_i: *Return on Equity – x_1, Cash Flow to Sales Ratio - x_2, Total Asset Turnover – x_3.*

The indicators that reduce efficiency y_i*: Current Receivables Concentration y_1, Non-current Foreign Capital Repayment Period – y_2, Operating Cost Ratio – y_3.*

These are two groups of financial ratio indicators commonly used in financial analysis. We synthesized these indicators into one comprehensive performance indicator to objectively express the financial situation of the company, focusing on performance. From the efficiency indicators (x_i), we subtracted the values of the indicators that reduce efficiency (y_i). This gives us the net efficiency, referred to as the HGN Synthetic Indicator. Using this model, we performed a comparison of the results from four mining companies in the cited paper. We examined the impact of the financial ratio indicator, *Total Asset Turnover* (x_3), on the resulting value of the synthetic indicator, depending on asset prices (acquisition, residual).

This paper focuses on the early indication of impending bankruptcy through the predictive capabilities of the HGN model. Although the model, in its basic version and some modified versions, has been verified on several companies, it will be necessary to adapt it to the heterogeneous conditions of non-financial businesses. Given the current turbulent environment, no predictive model can universally anticipate the financial development of companies by abstracting from specific conditions. For example, significant changes in the automotive industry, tightening environmental requirements, pandemics, and war conflicts, etc.

We assume that the application of the modified version of the HGN model has the potential to contribute to meeting the current European Union requirements for creating national systems for early indication of impending bankruptcies in Slovakia. With this paper, we aim to contribute to improving the system for indicating future adverse financial situations.

Results

The HGN model, in its basic version, functions quite accurately as a performance model for non-financial companies achieving profit. From the method of calculation and the content of the individual indicators, it logically follows that the company with the highest value of the synthetic indicator will achieve the highest performance. Previous research, verified on several companies, has confirmed this. However, in its basic version, the model is insufficient for the purpose of early identification of impending bankruptcy.

The HGN model significantly takes into account the debt situation of the company. It is sufficient for identifying bankruptcy, but it may not be entirely adequate for detecting imminent bankruptcy within a period of 1-2 years. The HGN model focuses on non-current debts within the company. Inability to repay any debts—whether non-current or current, bank loans or trade debts—is the most common cause of a crisis situation, which often leads to bankruptcy. We are aware of the high emphasis placed on the inherent indicator, the repayment period of non-current debts, in the current basic version of the HGN model. The requirements for early indication of impending bankruptcy will not be met by the HGN model in its current form. Several companies, whose insolvency led to bankruptcy, did not have non-current debts and thus could not attribute their bankruptcy to them. Their bankruptcy was caused by the inability to repay current debts. The basic version of the HGN model maximally considers the undesirable non-current debt situation as a negative factor. The value is expressed in the number of years required for the company to repay the debt from profit and depreciation. This significantly affects the final value of the synthetic HGN indicator. In a crisis situation, if the company does not generate profit and incurs a loss, it loses depreciation as a source of financing (part or even all of the depreciation, if the loss exceeds the depreciation).

The prediction of impending bankruptcy using the HGN model will be documented on a company that went bankrupt. However, finding an optimal solution will not be possible. We will attempt to confirm or refute the irreversible threat of bankruptcy of such a company based on publicly available data. Additionally, we will assess whether timely preventive measures could have saved the company. The analysis can only be conducted using publicly available data, such as financial statements and financial reports processed from the Finstat database.

From publicly available sources, we have data on the company SABAR, s.r.o., which underwent a court-approved restructuring and ultimately went bankrupt. In terms of SK NACE, the company was classified in the sector "Mining of chemical and fertilizer minerals 08.91.0." SABAR was established on July 1, 1999, as a continuation of long-standing predecessors and developed its business activities in three main areas: i) production of plastic windows and doors, ii) processing of waste materials, mainly fly ash, and iii) mining and processing of baryte products, which formed the core of its business. Baryte, a mineral characterized by its high density and composed of barium sulphate, is one of the rare raw materials in Europe, with only a few mines engaged in its extraction. On a global level, over 70% of baryte is used as a weighting agent in drilling fluids for oil and gas exploration. In Central and Eastern Europe, however, it finds application primarily in construction (e.g., in power plants and hospitals) and in the automotive industry (e.g., in brake systems and rubber mats).

We examine data for the period from 2013 to 2018. As documented in Table 1 on absolute indicators, the company, until 2015, achieved, although not very successful, overall positive standard results that could have been improved with timely measures. In 2014 and 2015, SABAR, s.r.o. employed more than 100 employees. Despite its diversified activities, the company encountered problems after years of operation. The main factors contributing to the financial crisis of the company were the decline in oil and gas extraction in Central and Eastern Europe, competitive pressure from baryte suppliers in Morocco and Turkey, as well as the overall decline in demand in the construction sector. These circumstances led to a drop in baryte prices on the market.

The data in Table 1 and the following Figure 1 highlight the development of selected absolute indicators. SABAR, s.r.o. encountered financial difficulties in 2016, when it started reporting a loss. The unfavourable results led to the company's restructuring. In 2017, the relevant court allowed the company to undergo restructuring and confirmed the restructuring plan in 2018. The restructuring under the supervision of the court and administrator led to a reduction in the company's original current debt by 66.7% between 2017 and 2018, with trade debt making up 60% of that amount. The repayment schedule for the remaining amount was spread over five years. At the end of 2019, based on a creditor's proposal, the relevant court declared bankruptcy on the debtor.

Tab. 1. SABAR s.r.o. Absolute Indicators of HGN for the Period 2013–2018

ABSOLUTE INDICATORS (€)	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Net Profit	43 632	39 649	60 888	-24 993	-420 703	362 540
Equity	695 913	737 221	792110	767 1160	346 413	710 613
Depreciation	14 595	12 414	4 155	7 762	6 692	6 239
Sales	3 000 282	3 287 812	2 748 350	1 906 443	1 595 380	1 810 963
Total Assets at Acquisition Cost	1 628 502	2 053 82200	1 988 955	2 207 465	2 224 683	2 080 671
Current Receivables	897 673	1 410 600	1 313 921	738 014	566 289	579 984
Non-current Liabilities	3 581	3 987	1 739	302	-283	1 658
Current Liabilities	464 217	808 808	674 800	685 764	991 176	660 722
Costs	2 854 005	3 199 908	2 704 637	2 468 579	2 137 983	1 961 744
Costs excluding Depreciation and Personnel Costs	1 512 374	1 925 393	1 427 392	1 200 569	894 519	964 738

The company in question went through a crisis, restructuring, and ultimately ended up in bankruptcy. The aim of this paper is to explore the possibilities for predicting imminent bankruptcy that could be used in an early warning system. For this purpose, we have selected the company SABAR, s.r.o.

The HGN model was tested as a performance model. Tests on several profitable companies confirmed its predictive ability in terms of performance. Our aim is to meet the current requirements for early warning systems for adverse financial situations of companies and, ultimately, the impending bankruptcy of a company. We will attempt to find a precise method for detecting impending bankruptcy and thus contribute to the early warning and detection system for looming bankruptcies. We consider SABAR s.r.o., based on its development from 2016 to 2018, to be suitable for this purpose.

In Table 1, we present the results from 2013 to 2018. It includes absolute indicators that serve as input indicators for calculating the basic financial ratios of the HGN model in its basic version. We have also added data on the volume of current liabilities, which were subject to restructuring in 2017. In the basic version of the HGN model, non-current debts are considered, as they are often a cause of adverse financial situations for companies. However, in the tested company SABAR, s.r.o., non-current debts did not represent a significant volume during the period in question. If we abstract from current debts, the results using the HGN model would not indicate a particularly adverse financial situation. The HGN model focuses on a company's debt situation from the perspective of the long-term time horizon. Therefore, it is necessary to seek the fundamental causes of the adverse financial situation in other indicators and, if needed, adapt the HGN model to the conditions of short-term indebted companies and modify the model in these respects.

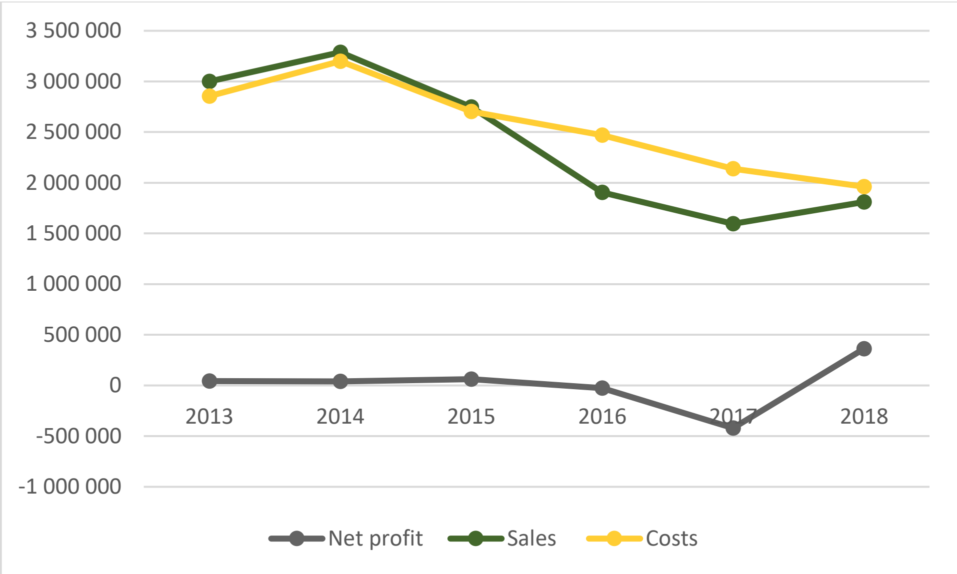

Fig. 1. SABAR s.r.o. Absolute indicators: Sales, Net profit, Costs

Based only on the basic absolute indicators of sales, profit, and costs, a decline in production began as early as 2014, followed by a decreasing volume of sales. Profit decrease occurred after 2015. The reduced decline in production is reflected in the decreasing costs, which will have a generally positive effect on the results. The development of sales and profit shows a negative trend, which will be appropriately assessed by the HGN model. Financial ratio indicators will provide more informative insight.

Table 2 contains the resulting values of the financial ratio indicators of the basic version of the HGN model.

Tab. 2. SABAR s.r.o. Financial Ratio Indicators of the HGN Model for the Period 2013-2018.

HGN – RATIO INDICATORS		**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
x_1	Return on Equity	0,0627	0,0538	0,0769	-0,0326	-1,2145	0,5102
x_2	Cash Flow to Sales Ratio	0,0194	0,0158	0,0237	-0,0090	-0,2595	0,2036
x_3	Gross Total Asset Turnover	1,8424	1,6008	1,3818	0,8636	0,7171	0,8704
y_1	Current Receivables Concentration	0,2992	0,4290	0,4781	0,3871	0,3550	0,3203
y_2	Non-current Debt Repayment Period	0,0615	0,0766	0,0267	-0,0175	0,0007	0,0045
y_3	Operating Cost Ratio	0,9512	0,9733	0,9841	1,2949	1,3401	1,0833

From Table 2, the contours of a prediction of adverse financial development for the analysed company are evident. A high volume of receivables predicts insufficient cash flow. As early as 2014, 43% of receivables were immobilised in unpaid sales. From the monitored year 2013 to 2018, the company did not have profits available (losses occurred in 2016 and 2017). While profits were reported in accounting, they did not materialise in cash income, making any repayments from profits as a fundamental source of long-term financing impossible. Results measured by the synthetic indicator HGN indicate a deteriorating trend starting in 2014, gradually culminating in 2017. Some predictive models suggested a positive or non-deteriorating trend, such as the Binkert model (Table 4, Graph 2). However, the HGN model, even in its basic version, unequivocally indicates a worsening trend, even though its content does not take into account current debts, which were significant. By modifying the HGN model, we aim to achieve a higher predictive ability to detect imminent insolvency in a timely manner. From Table 2 and Graph 2, it is clear that until 2016, no model, including the basic version of the HGN model, indicated a fundamentally worsening trend or imminent insolvency. Although a slightly deteriorating tendency, particularly in the values of the synthetic indicator HGN during 2015 and 2016, is apparent. In 2017, when a significant downturn occurred, all models indicated a very unfavourable financial situation. Unfortunately, this was already too late, as insolvency effectively occurred in 2017. Therefore, it is necessary to look for possibilities to modify the HGN model, adapting it to the conditions of the analysed company and accentuating the weaknesses of the adverse trend more significantly.

Tab. 3. SABAR s.r.o. Aggregated Indicators and Synthetic Indicator HGN 2013–2018

Aggregated Indicators and Synthetic Indicator HGN	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Aggregated Efficiency Indicator	1,9245	1,6704	1,4823	0,8220	-0,7568	1,5842
Aggregated Indicator Reducing Efficiency	1,3119	1,4789	1,4889	1,6645	1,6957	1,4080
Synthetic Indicator	0,6125	0,1916	-0,0066	-0,8424	-2,4526	0,1762

In the case of the tested company SABAR, s.r.o., unlike many other companies, non-current debts are not a fundamental problem, as they do not exist. The issue lies with current debts, which accounted for 62% of sales before restructuring. The share of current debts in sales is presented because the source of financing for current debts should be part of the sales corresponding to the respective costs. It should not be profit and depreciation, which should serve as sources of financing for long-term plans, especially investments.

Current debts largely consist of trade payables, which accounted for 73.3% of total current liabilities in the analysed company in 2017. This fact needs to be considered in the HGN model. The basic HGN model does not take this into account, so it is necessary to reflect this specificity in the model. To this end, we will modify the model. Specifically, in indicator y_2, which in the basic model expresses the repayment period of non-current debts, we will substitute current debts for non-current debts in the numerator.

The denominator in the basic model includes profit and depreciation as sources of financing for non-current debts. Financing current debts from profit and depreciation is not an appropriate approach in financial management. In the tested company SABAR, s.r.o., this would not even be possible. In 2017, the company recorded a loss. Depreciation is negligible. The achieved loss significantly exceeds the amount of depreciation. The original y_2 indicator thus loses its explanatory value in the HGN model.

Tab. 4. SABAR s.r.o. Financial Indicators 2013 – 2018

Prediction Models	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Altman Z-Score	3,67	2,96	2,90	1,89	0,73	2,61
Binkert Model	2,09	3,99	4,55	5,25	1,13	1,37
Bonity Indicator Model	1,23	0,89	1,11	0,17	-3,72	4,19
Taffler Model	0,75	0,63	0,63	0,39	0,16	0,74
Synthetic Indicator HGN in Basic Version	0,61	0,19	-0,01	-0,84	-2,45	0,18

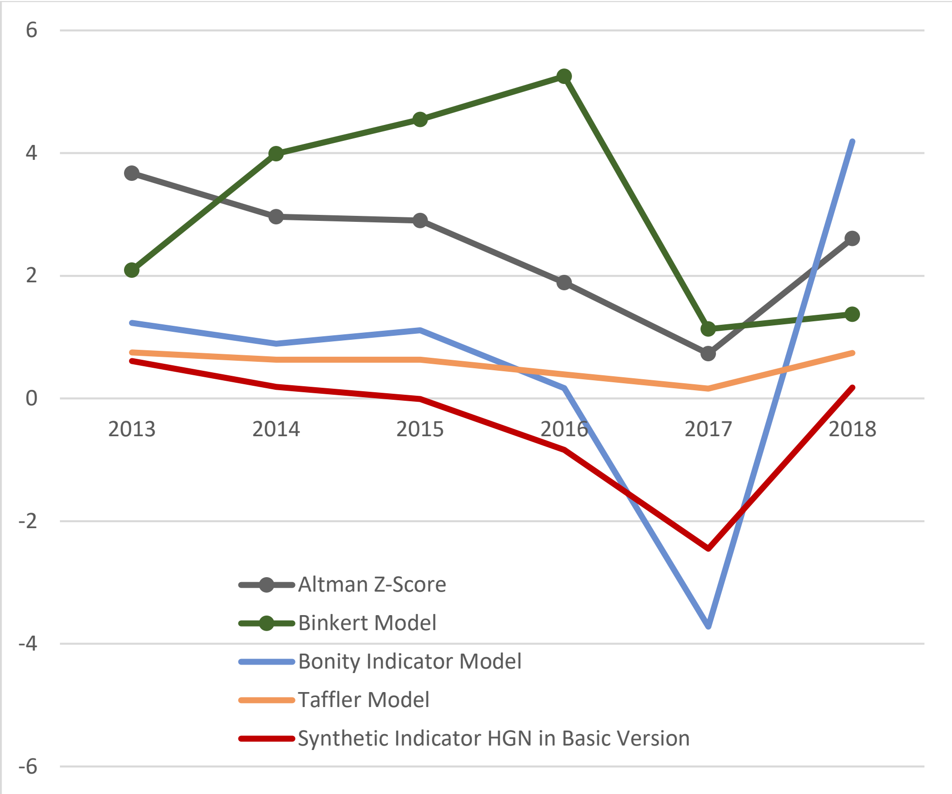

Fig. 2. SABAR s.r.o. Financial Indicators – Comparison of Development Trends 2013–2018

Graph 2 shows a comparison of the results of selected predictive models with HGN in its original version. Graph 2 clearly documents the development of values of individual predictive models. The purpose of this paper is to seek possibilities for objective prediction of impending insolvency. Which of the models presented in Table 4, or in Graph 2, can be considered reliable in predicting impending insolvency? Each model significantly detects the financial crisis and essentially insolvency in 2017, when insolvency was actually taking place in the company. Most of them indicated a deteriorating financial situation as early as 2016, but this cannot be considered a sufficiently timely prediction. In order for a model to be considered reliable in its predictive capability, we need to identify the impending insolvency earlier, in our case, no later than the results from 2015. The data shows that none of the models listed in 2015 show deteriorating results, except for the HGN model. The HGN model clearly indicates an unfavourable development starting from 2014. The value of the Synthetic Indicator has a declining tendency, unlike all other model values. Its basic version suggests an unfavourable prediction of development starting from 2014. However, despite this, we do not consider the model in its basic version to be sufficiently predictive for the purpose of identifying impending insolvency for a company like SABAR, s.r.o. The company does not use non-current loans and does not have non-current trade payables, which are a common cause of insolvency for many companies due to insufficient creation of financing sources.

In order to eliminate some attributes of the HGN model that inadequately express the debt situation of the tested company SABAR, s.r.o., we will develop a modified version of the model that more objectively and precisely represents the detection of impending insolvency. Following the above, we will substitute the indicator "Non-current Debt Repayment Period y_2" with "Current Debt Repayment Period y_2". The denominator will need to be substituted with an indicator that more objectively reflects the company's debt situation. Financing for current debts will be sourced from costs. The costs will then need to be rectified for depreciation and personal costs. The indicator would be substituted for these specific purposes as the ratio of current debts to costs excluding depreciation and personal costs. The high volume of current debts will be reflected in the indicator y_2, "Current Debt Repayment Period". Their financing source will not be profit and depreciation, but part of the sales. More precisely, current liabilities will be financed from costs after deducting depreciation and personal costs. The development of the volume of current liabilities was already unfavourable in 2014 and 2015. In 2014, it was around 40%, and in 2015, around 34%.

In the modified version of the HGN model for predicting impending insolvency for the company SABAR, s.r.o., it proves to be an appropriate and desirable solution to consider the volume of current debts instead of non-current debts. The company did not use non-current debts during the observed period, and therefore they cannot be the cause of the unfavourable financial situation. For the calculation of the Synthetic Indicator HGN, we will use current debts in the numerator and costs, excluding depreciation and personal costs, in the denominator. For this reason, we provide in Table 1 the values of these two absolute indicators, from which we will calculate the ratio indicator y_2, and subsequently the Aggregated Indicator Reducing Efficiency and the final Synthetic Indicator HGN.

Tab. 5. SABAR s.r.o. HGN Modified y_2 – Current Debt Repayment Period – Ratio Indicator, Aggregated Indicators, and Synthetic Indicator HGN 2013–2018

Modified Ratio Indicator **Aggregated Indicators and Synthetic Indicator**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
y_2 **Current Debt Repayment Period**	0,3069	0,4201	0,4728	0,5712	1,1081	0,6849
$\sum_{i=1}^{3} x_i$ - *Aggregated Efficiency Indicator*	1,9245	1,6704	1,4823	0,8220	-0,7568	1,5842
$\sum_{i=1}^{3} y_i$ *Aggregated Indicator Reducing Efficiency*	1,5574	1,8224	1,9349	2,2532	2,8031	2,0884
$SU = \sum_{i=1}^{3} x_i - \sum_{i=1}^{3} y_i$ ***Modified Synthetic Indicator***	0,3671	-0,1519	-0,4526	-1,4312	-3,5600	-0,5042

The substituted indicator y_2 significantly influenced the final value of the synthetic indicator in the individual observed years. In both cases, the synthetic value of the HGN indicator shows a downward trend from 2013. To assess the detection of impending insolvency, the years 2013 to 2015 must already be considered. The results of 2016 definitively confirm the threat of insolvency. Unfortunately, the information from 2016 is considered a late signal. Table 6 highlights the negative development in both groups of indicators (x_i and y_i) of HGN over the entire observed period. This cannot be said of the results of the other models listed in Table 4 and in Graph 2.

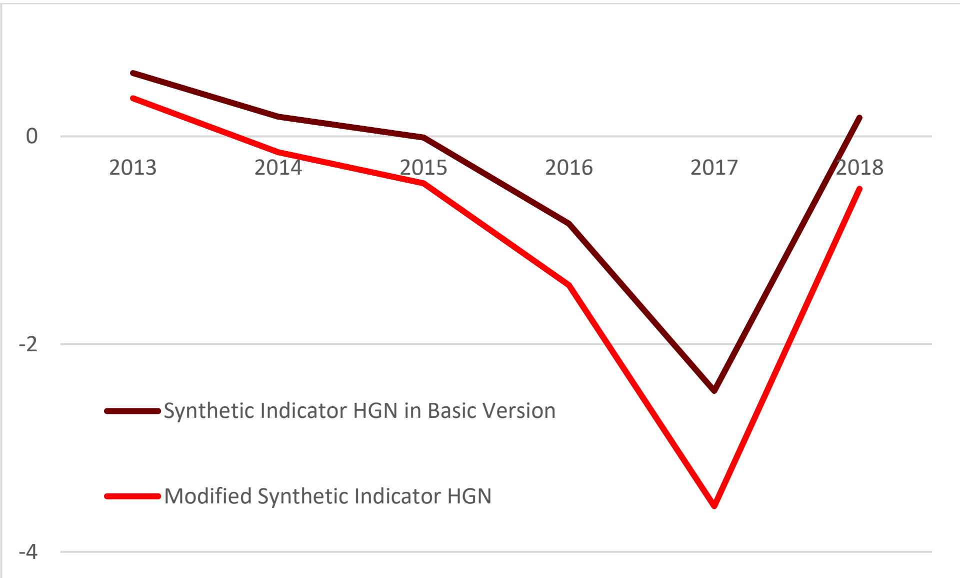

Fig. 3. SABAR s.r.o. HGN Modified y_2 –Current Debt Repayment Period – Financial Indicators – Comparison of Development Trends 2013–2018

Based on these presented results, we clearly recommend prioritising the HGN model as the model with predictive capability to detect impending insolvency. Financial problems inevitably translate into a lack of financial resources needed to finance investments and secure operations. The lack of financial resources in the HGN model is reflected by several indicators. We place emphasis on the debt situation, whether within the long-term or short-term time horizon. Multiple indicators have an immediate impact on the final value of the HGN model. Among the group of indicators, the most important is the indicator x_2 – *Cash Flow to Sales Ratio*. This indicator is part of the group of efficiency indicators, for which it is desirable that they be as high as possible, positively influencing the value of the Synthetic Indicator. In the case of low or no profit and depreciation, it does not positively affect the value of the Synthetic Indicator. On the contrary, it reduces its value. Another indicator that significantly affects the reduction of the Synthetic Indicator's value is y_1, the Current Receivables Concentration.

Excessive indebtedness does not necessarily mean impending insolvency. Debts can be a driver of business development. The problem arises when the business is unable to repay its debts on time. A warning sign of the inability to repay debts is insufficient generation of resources to service non-current and current debts. Another signal is also a high volume of receivables due to insufficient care for their collection. A high volume of receivables is the cause of insufficient cash flow, even despite generating a sufficient amount of profit. The HGN model takes into account these factors that affect its final Synthetic Indicator, and thanks to this, it detects impending insolvency in a timely manner. However, it is necessary to adjust the HGN model by modifying some indicators according to the specific financial situation. This is exactly what is presented in this paper through the analysis of financial results using the HGN model.

For comparison of the results of SABAR, s.r.o. with another non-financial company for the same period using the basic version of the HGN model, we will look at the results of ZEOCEM, s.r.o. The company ZEOCEM, s.r.o. achieved overall positive results, as assessed by financial indicators, during the same period. ZEOCEM, s.r.o. was deliberately selected because it belongs to the same industry as SABAR, s.r.o.

Tab. 6. ZEOCEM s.r.o. Absolute indicators of HGN for the period 2013–2018

HGN – ABSOLUTE INDICATORS (€)	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Net Profit	1 158 616	1 640 987	1 501 426	1 290 442	1 123 653	1 565 709
Equity	8 009 136	7 650 122	9 151 549	10 441 990	10 565 643	11 131 352
Depreciation	503 792	527 849	642 460	792 067	952 838	1 149 372
Sales	10 479 816	12 011 164	13 076 538	14 118 144	16 515 671	19 347 465
Total Assets at Acquisition Costs	10 068 172	9 969 467	12 895 812	14 024 867	15 194 475	24 055 746
Current Receivables	3 547 593	3 136 727	2 430 366	2 200 046	2 966 715	2 980 440
Non-current Liabilities	336 689	371 021	417 680	451 331	493 014	552 575
Current Liabilities	1 410 447	1 651 814	2 098 911	1 762 005	2 276 320	2 727 893
Costs	9 247 930	10 041 657	11 422 440	12 492 065	15 267 962	17 557 324

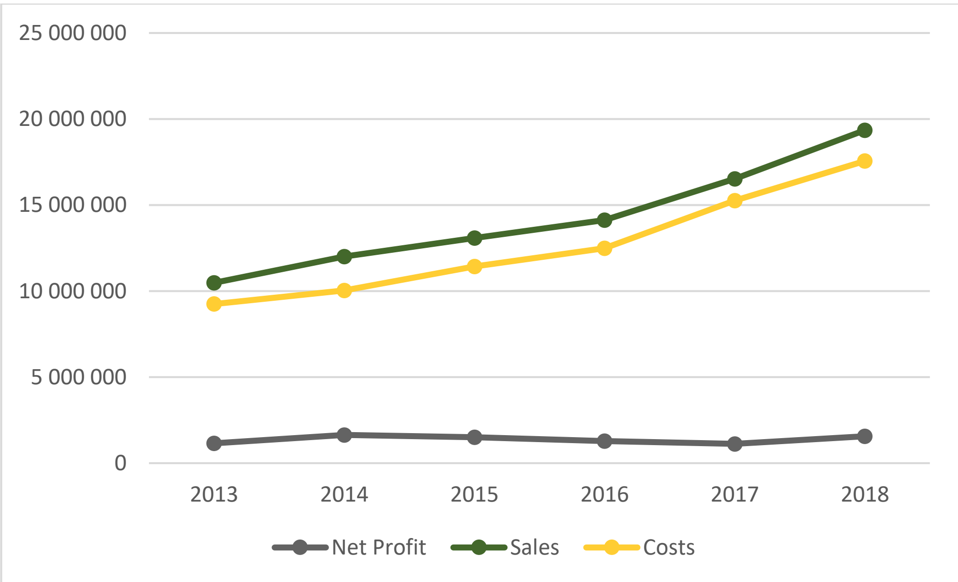

Fig. 4. ZEOCEM s.r.o. Absolute indicators Sales, Net profit, Costs

Tab 6 and Chart 4 provide information on the financial results of the company ZEOCEM, s.r.o. evaluated by selected indicators. We want to compare both companies using the HGN model, i.e. a company facing impending insolvency and a company with positive results. The company ZEOCEM, s.r.o. shows sales growth, i.e. sales, with appropriately rising costs, while maintaining a generally stable trend in profit achievement. In terms of financial performance, these are two different companies.

Similarly, we will apply the HGN model in its basic version to the company ZEOCEM, s.r.o. This is because the company has non-current debt in the evaluated period, generates profit annually, and also creates depreciation. To cover non-current debt, it generates financing sources in the form of profit and depreciation. The company SABAR, s.r.o. did not generate profit or depreciation, but also did not have non-current debt. However, it had a high volume of current debt and, due to insufficient receivables collection, a lack of cash flow. For this reason, it became insolvent. The modified version of the HGN model predicted the impending insolvency fairly in advance. The company ZEOCEM, s.r.o. is operating stably in the market in the current period, i.e. in 2024. The synthetic indicator and the aggregated HGN indicators do not signal financial problems for ZEOCEM, s.r.o. They assess the company's performance, and in terms of future development, HGN confirms the existence of predictive ability. For the company SABAR, s.r.o., the basic version of the HGN model signals impending insolvency, and in the modified version, it clearly confirms the acute risk of insolvency.

Tab. 7. ZEOCEM s.r.o. HGN required financial ratios 2013 – 2018

HGN - POMEROVE UKAZOVATELE		**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
x_1	Return on Equity	0,1447	0,2145	0,1641	0,1236	0,1063	0,1407
x_2	Cash Flow to Sales Ratio	0,1586	0,1806	0,1639	0,1475	0,1257	0,1403
x_3	Gross Total Asset Turnover	0,7540	0,8402	0,7329	0,7191	0,7632	0,8043
y_1	Current Receivables Concentration	0,3385	0,2612	0,1859	0,1558	0,1796	0,1540
y_2	Non-current Debt Repayment Period	0,2025	0,1711	0,1948	0,2167	0,2374	0,2035
y_3	Operating Cost Ratio	0,8825	0,8360	0,8735	0,8848	0,9245	0,9075

Tab. 8. ZEOCEM s.r.o. Aggregated Indicators and Synthetic Indicator HGN 2013 – 2018

Aggregated Indicators and Synthetic Indicator HGN	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Aggregated Efficiency Indicator	1,0573	1,2353	1,0609	0,9901	0,9953	1,0853
Aggregated Indicator Reducing Efficiency	1,4235	1,2682	1,2542	1,2574	1,3415	1,2650
Synthetic Indicator	**-0,3662**	**-0,0330**	**-0,1933**	**-0,2672**	**-0,3462**	**-0,1798**

Positive results for the company ZEOCEM, s.r.o. are also documented in Table 9 and Chart 5. Based on the results from 2013 to 2018, a positive development can be expected even after 2018. Further development confirms this trend.

Tab.9 ZEOCEM s.r.o. Financial indicators HGN 2013 – 2018

Prediction Models	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Altman Z-Score	3,86	3,74	3,25	3,69	3,33	3,27
Binkert Model	2,02	1,94	2,17	1,72	1,88	1,86
Bonity Indicator Model	3,91	4,88	3,51	3,04	2,43	2,83
Taffler Model	1,10	1,17	0,89	0,91	0,72	0,77
Synthetic Indicator HGN in Basic Version	-0,37	-0,03	-0,19	-0,27	-0,35	-0,18

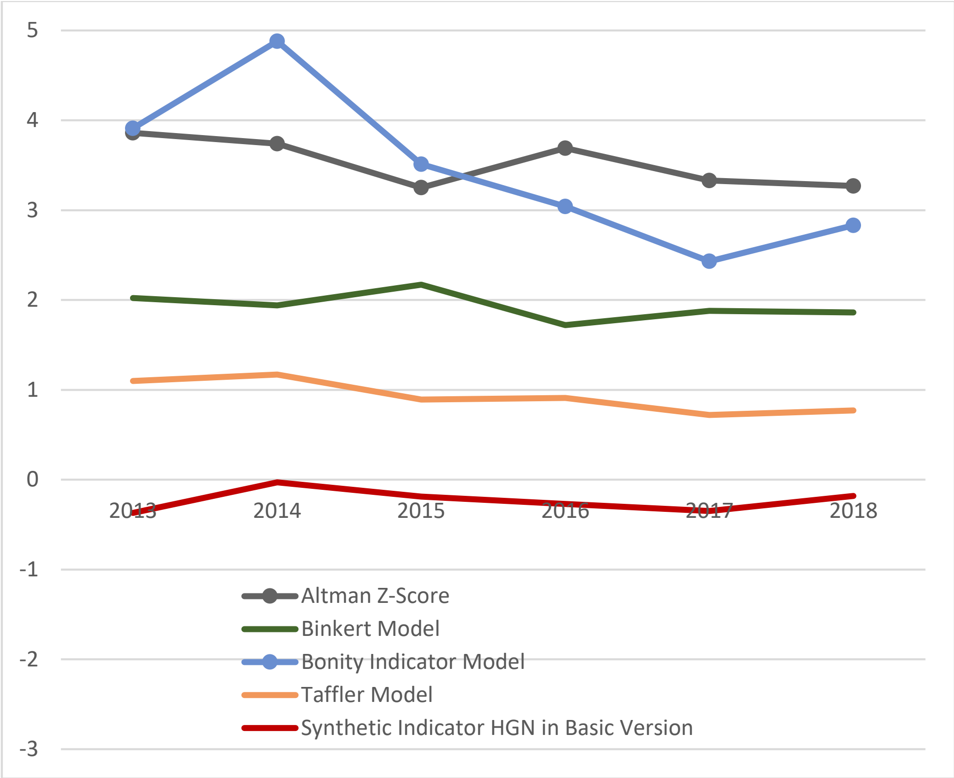

Fig. 5. ZEOCEM s.r.o. Financial indicators - comparison of development trends 2013 – 2018

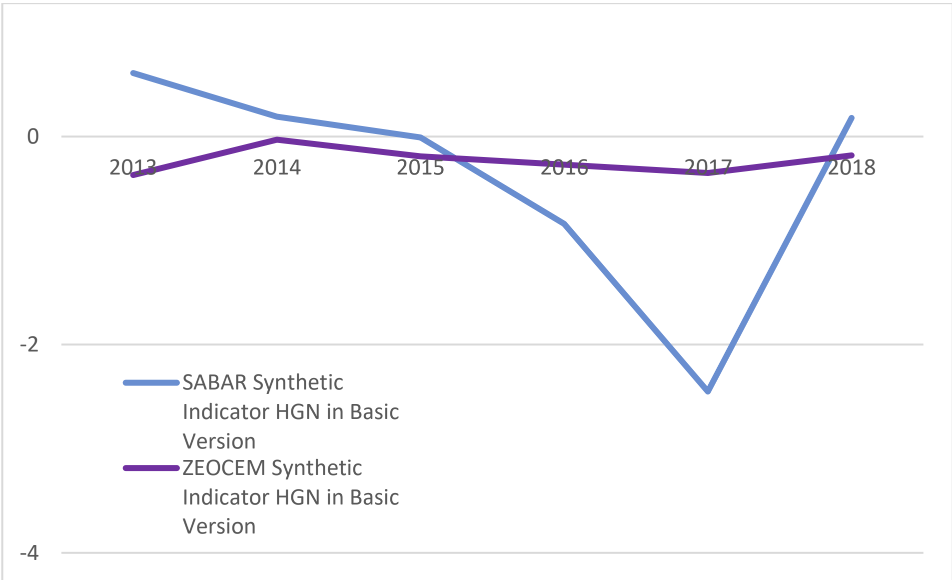

Fig. 6. SABAR vs. ZEOCEM s.r.o. Financial indicators - comparison of development trends 2013 – 2018

Discussion

The presented analysis provides an insight into the issue of predicting impending insolvency through the application and subsequent modification of the HGN model. The results of the analysis of the tested company SABAR, s.r.o. clearly indicated that the basic version of the HGN model has the ability to generally point out long-term adverse trends. In industries where short-term indebtedness and cash flow problems are considered dominant risk factors, the predictive attribute of the model in its basic version, i.e. its ability to predict impending insolvency, is reduced. For the purposes of early identification of impending insolvency, its adaptation is essential to implement these determining factors into the model. This requirement was sufficiently met by altering or modifying the model, specifically by eliminating one indicator and replacing it with a financial ratio that takes key determinants into account. The original indicator, which considered the repayment period of non-current debts, is considered redundant in the examined industry and especially in the tested company. This indicator, in this case, i.e. under the conditions of the analysed company, does not have sufficient explanatory power and loses its justification. The reason is the absence of non-current debts, profit, and depreciation. Therefore, we consider it unnecessary when evaluating the subject in question.

The added value of the modified HGN model is the substitution of the original indicator (*y2*) "Non-current Debt Repayment Period" with the "Current Debt Repayment Period" indicator. This adjustment reflects the need to analyse the sources of financing for current liabilities, which have proven to be a critical determinant of the financial stability of the company SABAR, s.r.o. The results clearly point to the fact that ignoring current debts in the basic version of the model could lead to incorrect conclusions about the financial health of the company. The modified version of the HGN model took into account costs adjusted for depreciation and personal costs, ensuring greater accuracy in evaluating the ability to repay current liabilities. The substitution allowed for a significantly more objective increase in predictive accuracy. This model adjustment identified a deteriorating trend as early as 2014, which is a significantly earlier signal compared to other models used in the analysis.

In the application of the HGN model to the company SABAR, s.r.o., it was evident that adverse trends were clearly identifiable as early as the 2014–2015 period. This indicates a higher potential for early warning of impending insolvency. Traditional predictive models, such as Altman's Z-score, Taffler's model, and others, showed the ability to detect the deteriorating situation only in 2016. In the case of the analysed company SABAR, s.r.o., this was no longer early enough. The window for preparing and implementing preventive measures is thus reduced. This comparison highlights the more accurate predictive ability of the modified HGN model under specific conditions compared to other models.

An important finding of this contribution is also the need to differentiate the approach when evaluating different types of companies. The company ZEOCEM, s.r.o., demonstrated stable results due to effective cash flow management and lower levels of current liabilities. The results of the company SABAR, s.r.o., highlighted the necessity of more intensive consideration of short-term risks. This proves that the universality of the HGN model in its basic version, as well as other commonly used predictive models, is limited. Their effectiveness depends on the ability to adapt to the specifics of individual sectors and business situations.

The findings also raise questions regarding the further methodological optimization of the HGN model. The goal is for it to be capable of providing even more accurate and comprehensive outputs. Special emphasis needs to be placed on integrating qualitative factors, such as managerial decisions or macroeconomic influences, which can significantly impact the financial health of a company. Implementing these requirements in a way that fully accounts for the objective assumptions necessary for the adoption of preventive measures in any model is, however, quite challenging.

It should be emphasized that no predictive model can rigorously forecast insolvency or even an impending insolvency. It can hypothetically indicate financial problems that could lead to insolvency. This contribution also points out that hypothetical assumptions should be documented by multiple forms of indication. These methods could be part of an early warning system. For this reason, we have also included results obtained using multiple predictive models. If predictions of impending insolvency are confirmed or supported by similar results from other models with predictive ability, it is a clear signal for the necessary adoption of fundamental measures leading to preventive restructuring. In generalizing the results achieved, the results obtained using the HGN model and its relevant modification for specific conditions could then serve as a primary and decisive argument for further financial decision-making by management in connection with preparing preventive restructuring of the company in line with current requirements.

Conclusions

The analysis we conducted in our article highlights that the HGN model has the potential to become part of the tools for early warning of impending insolvency not only in the Slovak Republic but also within the European context. Even the original version of the HGN model can contribute to more effective insolvency prevention and strengthening the financial stability of companies. The substitution of the indicator allowed for a more accurate consideration of determining undesirable impacts on financial stability. These include insufficient cash flows, high volumes of current debts, and the inability to repay them on time. Our verification, which tested the modified HGN model, confirmed that in this form, the model could represent a significant contribution to predicting impending insolvency of companies.

We must emphasize that it is necessary to adapt the model to the specific conditions of the industry or company in question. The application of the HGN model also revealed critical shortcomings of traditional predictive models. The modified approach of the HGN model helped to objectivize the picture of the future negative trend in financial results. This can be considered an undeniable advantage compared to other predictive models. The results we reached in this study provided a premise for further research in this area and could help improve predictive capabilities within similar tools such as the HGN model.

In a broader context, it can be noted that integrated early warning systems should combine multiple models in order to obtain a comprehensive picture of the financial situation of companies. Our findings could then, through their implementation into existing predictive models, serve as support for decision-making within the application of comprehensive early warning systems.

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