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ASSESSMENT OF THE APPLICABILITY OF FINANCIAL INSOLVENCY MODELS

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Abstract

This article aims to develop criteria for classifying the most commonly used financial diagnostic models based on the scientific literature related to the theoretical and methodological assumptions of financial insolvency. On this basis, we assess the models' applicability by considering the specifics of Bulgarian conditions - difficulties, limitations in their application, advantages and disadvantages. The practical study focuses on enterprises operating in the agricultural sector which allegedly have been the subject of bankruptcy proceedings. The authors attempt to reveal to what extent the diagnostics using financial sustainability analysis methods provide an accurate forecast of the risk of insolvency and, hence, bankruptcy. The present study seeks answers to the following questions: are there any methodologies that stand out with a highest degree of coincidence of the forecast with the actual status quo of "declared bankruptcies"? Which indicators are characteristic of the agricultural sector, and what makes the applicability of the methods in which they participate most suitable for testing?

Key words: *insolvency, classification bankruptcy prediction models - advantages and disadvantages, agriculture*

INTRODUCTION

Forecasting future bankruptcies always raises the question whether the choice of methodology is correct and to what extent financial analysts can trust it. It is no coincidence that the literature abounds with models for the *ex ante* detection of bankruptcy risk as developed by Altman (1968) [1], Altman (2000) [2], Yang (1999), [29], Kasarova (2010) [12], Mohammadi (2016) [22], Huo (2006) [10], Valashkova (2020) [27]. Each subsequent author looks for their application in a specific economic sector, explores national specificities, scope of analysis, etc.

The study of insolvency risk models is of key importance for agriculture, as it takes into consideration certain specifics. The sector has traditionally been regarded as high risk, with low creditworthiness of producers. To a large extent, agricultural activity is characterised by low profitability as affirmed Kuhmonen and Siltaoja (2022) [16]; European Commission, 2020 [7] and a high proportion of loss-making enterprises Lubenova (2012) [20]; Prisacaru, and Strainu (2023) [24]. These factors favour higher indebtedness of agricultural enterprises and the risk of deterioration of financial health and insolvency. Due to its importance and the need to satisfy the debts to creditors, the insolvency procedure is statutory.

Insolvency in Bulgarian legislation is governed by the Commercial Law. It states that "the purpose of insolvency proceedings is to ensure fair satisfaction of creditors and the possibility of reorganising the debtor's undertaking (Commercial Law, 1991) [5]. It is opened by application by the debtor company or its creditor. Where there is a debt to the State or the municipalities, it is also opened at the request of the National Revenue Agency. Applications to initiate insolvency proceedings is also published in the Commercial Register. Although the majority of companies are in insolvency proceedings, they continue to be active in trade.The aim of this study is to propose a classification of analytical models for bankruptcy risk assessment and by using real data to identify which of the selected models has the highest degree of forecast matching with the actual *status quo* of "declared bankruptcies".

Review of the Criteria classification

The variety of models provides grounds to classify them and to indicate their advantages and disadvantages.

After a thorough literature review: Kulchev, (2023) [17], Balina et al. (2021) [4], Valaskova and Gajdosikova (2021) [28], Milić et al. (2021) [21], Dorohan-Pysarenko, L. et al. (2021) [6], Korol (2019) [14], Popescu (2014) [23], Table 1 lists some of the more important criteria for classifying analytical models for bankruptcy risk assessment. Each of the plethora of models has its advantages and disadvantages over the others. For example, discriminant analysis models are distinguished by a high level of interpretability of the results, accuracy and simplicity (Kanapickienė, R., 2023)[11]. Artificial neural network models, on the contrary, are said to be more difficult and require more modelling skills (Zhang, 2016) [30]. The latter are used to model quite complex nonlinear dependencies, using a computer program that selects those indicators that have the greatest impact on bankruptcy (Haas, C., 2023) [9].

Table 1. Criteria for classifying analytical models for bankruptcy risk assessment

Criteria	Types	Criteria	Types
1. According to the methodology used	- discriminant analysis; - logistic regression; - artificial neural networks, etc.	6. According to the individual indicators included in the model	- liquidity - profitability - capital structure - others
2. By economic sector of application	- for the industry sector; - onstruction; - agricultural sector; - trade, etc.	7. According to the technique used to process the results	- statistically; - intelligent (artificial intelligence models)
3. According to the scope	- global (applicable to all countries); - applicable at national level	8. According to the nature of the information they use	- on the basis of micro data (most often on the basis of annual financial statements) - based on macro data (by reflecting market factors)
4. By enterprise size	- micro - small; - medium; - large	9. According to the time order of the forecast	- for long-term forecasts; - for short-term forecasts
5. According to the number of indicators involved in the model	- bifactor; - trifactorial; - tetra-factorial, etc.		

Source: own contribution.

Other studies rely on the better classification abilities of logistic regression models compared to those of discriminant analysis (Kovacova, Kliestik 2017) [15]. Another disadvantage of the linear discriminant analysis model is that microeconomic factors are analyzed without considering the macroeconomic environment (Kiyak, 2012) [13].

What matters when choosing a model is the affiliation to a certain economic sector. According toValashkova (Valashkova, 2020) [27], models developed in a particular economic sector significantly outperform the predictive capabilities of other models adopted in the same country or abroad. For example, the peculiarities of the construction sector inevitably affect the performance of the model. Balina, R. argues that in order to remain solvent, firms in the construction industry need to maintain their level of profitability of current assets above the construction industry average. This is explained by the fact that firms in this sector use a significant amount of working capital in their daily operations (Balina, 2021) [4]. The agricultural sector stands out for its specificities, caused by the seasonal nature of its production. Its production and financial performance are also subject to weather and climatic conditions, as well as the length of the production cycle. The above factors can impact important financial indicators, such as turnover, liquidity, profitability and solvency. For example, the agricultural sector is characterized by low levels of profitability (Letyagina et al., 2020) [19]. At the same time, the subsidization of agricultural producers is reflected in the small number of firms that have declared insolvency.

The size of the enterprises whose data are analysed is also relevant for the results of the method applied. It turns out that, expressed in percentages, the predictive capabilities of insolvency risk assessment models are higher for enterprises that are classified as large or medium-sized, compared to small and micro-enterprises (Kanapickienė, R., 2023) [11]. One of the reasons is that in the case of micro-enterprises, for example, annual financial statements are simplified and the data contained in them is minimised - for example, they give information only on the sections, with none available for groups, items or analytical accounts. Therefore, for this group of companies it is difficult, and sometimes impossible, to apply any of the bankruptcy prediction models.

The use of financial ratios to determine the financial health of a company are a common tool in practice. Long-term solvency ratios involve equity, leverage, total capital, etc. Their purpose is to establish the participation of sources external to the firm to finance its activities. The ratio between equity capital and capital employed is relevant for the financial autonomy of the firm. According to Kasarova (Kasarova, 2010) [12] capital structure ratios, reveal the financial stability and independence of the company from its creditors. However, too high a proportion of equity may lead to a decrease in the profitability of equity.

The capital structure of a firm is also influenced by its size. It appears that smaller firms have more difficulty in accessing external financing than larger firms.

In this context, the purpose of the paper is to develop criteria for classifying the most commonly used financial diagnostic models based on the theoretical and methodological assumptions of financial insolvency offered by literature in the field. Also, we aim to assess the applicability of these models in the specific conditions of Bulgaria.

MATERIALS AND METHODS

The study includes anonymised micro data from sector "A" - Agriculture, Forestry and Fisheries from the Annual Enterprise Accounts for the period 2014-2023. They belong to the group of small and micro enterprises based on the attribute of number of employees. For the purpose of tracking over time, the enterprises included in the sample are coded for the whole period with the same identifier - from 1 to 14. By 2024, seven of them have been involved in insolvency proceedings and the remaining seven operate normally. According to the National Statistical Institute, there are no large or medium-sized enterprises in this sector that have declared insolvency as of this reporting period.

In order to investigate which models are applicable for establishing insolvency in agriculture, the authors focus on three models. The first of these is the Springate model, which they have already studied in previous publications and found that it predicts very high values of correctly classified enterprises in the group of "Financial Crisis and Bankruptcy" businesses (Stoyancheva and Angelova, 2024) [25]. It is also very sensitive to the deterioration of the financial health of firms in the agricultural sector and it will be appropriate to resort to some of the Eastern European models for greater certainty of the claim of bankruptcy (Angelova and Stoyancheva, 2023) [3]. This recommendation has been applied in this study by using two more models (both from Eastern European countries, Croatia and Bulgaria, respectively). The Croatian model is that of Kliestik, which is found in a publication by Valashkova (Valashkova, 2020) [27].

The above-mentioned model refers to a study on the risk of bankruptcy for enterprises in the agricultural sector classified as "small". The aim is to find as much consistency as possible in terms of national, sectoral and group affiliation within the analysed sample. Such is the motive for choosing the Kulchev model (Kulchev, 2023) [17],which was developed for Bulgarian conditions.

The financial ratios used and the corresponding bankruptcy risk estimates of the Springate, Kliestik and Kulchev's models have been presented in Table 2.

Table 2. Insolvency risk forecasting models

X	Springate	Kliestik	Kulchev
X1	WK/TA	NI/E	TA/TL
X2	EBIT/TA	(NCL+CL)/TA	E/TL
X3	EBT/CL	WK/S	(NI+AM)/TL
X4	S/TA	EBT/E	EBIT/TA
X5	-	-	E/TA
X6	-	-	(CA-I)/CL
X7			CA/CL
	Z<0.862	Z>0	Z<12.546

Source: own contribution.

where:
WK - Working Capital;
TA - Total Assets;
EBIT - Earnings Before Interest and Taxes;
TL - Total Liabilities;
S - Sales;
EBT - Earnings Before Taxes
CL - Current Liabilities
NCL - Non-current Liabilities
CA - Current Assets
NI - Net Income
E - Equity
I - Inventories
DE - Depreciation Expenses

Springate's test model contains four variables (Todorov, 2014) [26]:

$$Z = 1.03 * X1 + 3.07 * X2 \pm 0.66 * X3 \pm 0.4 * X4$$

Kliestik's Model (Valashkova, 2020) [27] proposes four other financial ratios specifically aimed at the valuation of small businesses.

$$Z\ S\ NACE\ A = -1.412 - 1.512 * X1 + 2.504 * X2 - 0.06 * X3 + 1.256 * X4$$

Kulchev's Model (Kulchev, 2023) [17] uses seven financial ratios to identify the risk of insolvency.

$$Z = 9.3187 * X1 + 9.3021 * X2 + 9.1257 * X3 + 6.1674 * X4 + 2.6852 * X5 + 0.38308 * X6 + 0.32977 * X7$$

Data description

We used data from the financial statements of the companies which allows us to track and compare some indicators relevant to their financial health. All the enterprises insolvent in 2023 and 2024 had higher total assets for the period 2014-2020 (Table 3).

In the following years, the assets of the enterprises decreased sharply, coinciding with the insolvency of a large number among them. Financially healthy enterprises showed a smooth and steady increase in average assets.

Over the period under review, we observed a number of changes in financial data and ratios indicating unfavourable trends for enterprises with poor financial health (Table 3).

– The average total liabilities exceed more than twice the financially healthy companies. At the same time, we observe that their value has doubled - from BGN 1,076 thousand to BGN 2,230 thousand. The results are also applicable when distinguishing between long-term and short-term liabilities. Liabilities up to one year increased more gradually, but in the last 3 years they rose sharply in value. Bankrupt firms maintained a higher level of borrowed capital.

– Significant differences are observed when comparing working capital data. Its magnitude is more than three times the working capital of financially sound enterprises until 2019. This result corresponds to a sharp increase in short-term liabilities. By 2020, the insolvent 2023 enterprises can no longer pay their liabilities with current assets, and signs of deteriorating financial health and delayed payments emerge.

– The contraction in working capital is manifested in two directions - a reduction in inventories and receivables from suppliers and customers. By 2019, insolvent companies disclose a significant volume of inventories exceeding those of financially sound companies. The subsequent deterioration in financial health indicates that this volume exceeds a healthy level of inventories and maintaining it has adverse consequences.

– The comparison of the average size of claims highlights some differences. For both groups of enterprises, receivables are increasing in size, but for financially healthy enterprises, the increase is slower and somewhat uneven over the years. However, for insolvent firms, claims increase sharply until 2019, signaling a delay in payments and the presence of inter-firm indebtedness.

Table 3. Selected indicators from the financial statements of enterprises

State	2014	2016	2018	2020	2022	2023
Total Assets						
1	4,105	4,043	4,325	2,300	1,221	1,056
2	1,646	2,282	2,561	2,990	4,110	4,639
Total liabilities						
1	1,076	1,002	1,919	2,134	1,935	2,230
2	527	639	712	620	523	680
Working capital						
1	1,608	1,739	2,102	-389	-745	-758
2	551	510	498	711	2,030	1,216
Inventory						
1	982	850	1,019	222	229	216
2	538	452	492	732	901	1,271
Receivables						
1	41	79	243	82	26	23
2	21	16	83	78	187	95

Source: own calculations.
where: 1 - bankrupt companies; 2 - financially sound enterprises

Table 4 presents financial leverage ratios commonly used in practice and theory (Kulchev, 2023a) [18], Valaskova and Gajdosikova, 2021) [28] Gajdosikova, D. et al, 2023 [8]).

Table 4. Debt ratios of insolvent firms

2014	2016	2018	2020	2022	2023
Current assets/Short-term Liabilities					
6.57	4.68	4.64	5.78	1.01	42.28
(Current assets-Inventory)/Short-term Liabilities					
3.60	3.13	3.02	1.15	.64	1.59
Equity/Total liabilities					
1.12	2.17	1.88	.25	-.25	-.60
Equity/Total assets					
.35	.42	.35	.08	-2.09	-3.28
Gross profit/Short term liabilities					
2.70	.46	.20	.19	.07	0
Total liabilities/Equity					
2.97	2.54	7.27	4.62	14.93	-7.10
Total liabilities/Assets					
.61	.50	.63	.93	3.11	4.18

Source: own calculations.

The liquidity indicators attest to elevated values above the recommended ones throughout the period.

The results show that the enterprises have frozen funds in the form of a significant amount of inventories.

The corresponding values of the ratios are - quick ratio above 1, and current ratio - above 2.

The financial leverage ratios signal that insolvent firms finance their activities mainly with borrowed capital. The total liabilities to equity ratio remained above 2 in all years, reaching extreme values of 9 and 14.

The total liabilities to assets ratio shows that the share of liabilities exceeds the recommended 30-60% of total assets, except for the years 2015-2017.

RESULTS AND DISCUSSIONS

The results of the analysis using the Springate model are shown in Table 5.

The data in Table 5 are arranged horizontally by years from 2014 to 2023 and vertically by the coded name of the enterprise from 1 to 14. After the calculations, the results are sorted against the year 2024, for which there is information that the indicated enterprises are undergoing insolvency proceedings.

For the period 2014-2023, for all the analysed enterprises, the risk of insolvency is reported as "F", and the risk of insolvency as "No". The Springate model succeeds in capturing the bankruptcy risk in the longer term for all enterprises that are in insolvency proceedings. Since it is very sensitive to the financial health of firms, it gives indications even for firms that are not in such a procedure and are developing normally.

As mentioned above, the data refer to micro and small enterprises in the agricultural sector. The provision of subsidies in this sector manages to blur the picture of the analysis, especially for micro-enterprises, which have already been mentioned as using simplified financial statements. In the short term, for the last two years, the forecast of insolvency coincides 100% with the actual *status quo* for enterprises that have declared bankruptcy.

The results of the analysis using the Kliestik model are shown in Table 6.

Table 5. Results - Bankruptcy risk determined by the Springate's model

AE	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
2	F	F	F	F	F	F	F	F	F	F	Ins
3	H	H	H	H	H	F	F	F	F	F	Ins
5	F	F	F	F	F	F	F	F	F	F	Ins
6	F	F	F	F	F	F	F	F	F	F	Ins
7	H	H	F	F	H	H	F	F	F	F	Ins
10	H	F	H	F	F	F	H	H	F	F	Ins
11	H	F	F	F	F	F	F	F	F	F	Ins
1	H	H	H	H	H	H	H	H	H	H	
4	H	H	F	H	F	F	F	F	H	H	
8	F	F	F	F	F	F	F	F	F	F	
9	F	F	F	F	F	H	H	H	H	H	
12	H	H	H	F	H	H	H	F	H	H	
13	F	F	H	F	F	F	F	F	H	H	
14	F	F	F	F	F	F	F	H	H	F	

Source: own contribution
where: F – failed; H – Healthy; AE - Agricultural Enterprises; Ins - Insolvency

Table 6. Results - Bankruptcy risk determined by the Kliestik's model

AE	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
2	H	F	F	F	F	F	F	F	F	F	Ins
3	H	H	H	H	H	H	F	F	F	F	Ins
5	F	F	F	F	F	F	F	F	F	F	Ins
6	F	F	F	F	F	F	F	F	F	F	Ins
7	H	H	H	H	H	H	H	H	F	F	Ins
10	H	F	H	F	F	H	F	F	F	F	Ins
11	F	F	H	H	F	F	F	F	F	F	Ins
1	H	H	H	H	H	H	H	H	H	H	
4	H	H	H	H	H	H	H	H	H	H	
8	F	F	F	F	F	F	F	F	H	F	
9	F	F	F	F	F	F	H	H	H	H	
12	F	H	H	H	H	H	H	H	H	H	
13	F	F	F	F	F	F	F	H	H	H	
14	H	H	H	H	H	H	H	H	H	H	

Source: own contribution
where: F – failed; H – Healthy; AE - Agricultural Enterprises; Ins - Insolvency

Table 7. Results - Bankruptcy risk determined by the Kulchev's model

AE	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
2	H	H	H	H	H	H	F	H	F	H	Ins
3	H	H	H	H	H	H	H	F	F	F	Ins
5	H	H	H	F	F	H	F	H	F	F	Ins
6	H	H	H	H	H	H	H	F	F	F	Ins
7	F	H	H	H	H	H	H	H	F	F	Ins
10	H	H	H	H	H	H	H	H	H	F	Ins
11	H	H	H	H	H	H	H	H	H	F	Ins
1	H	H	H	H	H	H	H	H	H	H	
4	H	H	H	H	H	H	H	H	H	H	
8	H	H	H	H	H	H	H	H	H	H	
9	H	H	H	H	H	H	H	H	H	H	
12	H	H	H	H	H	H	H	H	H	H	
13	H	F	H	H	H	H	H	H	H	H	
14	H	H	H	H	H	H	H	H	H	H	

Source: own contribution
where: F – failed; H – Healthy; AE - Agricultural Enterprises; Ins - Insolvency

The results on the Kliestik model are also identical to the Springate model.

Again, we see a 100% match of the short-run forecast with the actual picture in terms of firms in bankruptcy. Again, this model is responsive to some of the fluctuations in financially sound firms, although in the short run they show a higher degree of predictability.

The results of the analysis using the Kulchev model are given in Table 7.

Kulchev's model offers a 100% accurate forecast for financially sound companies, and about 85.7% for those in bankruptcy.

The forecast is fully consistent with the summary recapitulation of the predictive capabilities of the analytical models with information for the last year of the analysis period (Kulchev, 2023 [17]).

This allows us to recommend combining this model, which was developed for Bulgarian conditions, with some of the other two models.

CONCLUSIONS

This study compares the accuracy of default risk estimates of the Springate, Kliestik and Kulchev models for their application in the agricultural sector.

A number of available models produce inconsistent results when tested for the insolvency risk of agricultural enterprises. Our results show that these three models provide correct predictions, exhibiting different estimation sensitivities and allowing for a deeper financial analysis.

Springate's model exhibits the greatest valuation sensitivity and classifies firms as potentially risky several years before actual insolvency occurs.

Very close to these forecasts are the Kliestik model estimates. Both models manage to predict 100% of the insolvent firms in the last two years - 2022-2023.

Kulchev's model also shows very high forecast accuracy for both years, failing to forecast insolvency for only one firm.

Overall, Kulchev's model is less sensitive to the temporal variation of financial ratios across years, but with high forecast accuracy.

In conclusion, the obtained results prove with sufficient confidence that the proposed three models correctly classify agrarian businesses in bankruptcy and it is appropriate to use them simultaneously for higher forecast certainty.

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REFERENCES

[1]Altman, E.I., 1968, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bancruptcy. The Journal of Finance, 23(4). 589-609.

[2]Altman, E.I., 2000, Predicting financial distress of companies: revisiting the Z-score and ZETA models. - Stern School of Business, New York University Working paper, p.1-54. http://pages.stern.nyu.edu/~ealtman/zscores.pdf. Accessed on 17.01.2025.

[3]Angelova, R., Stoyancheva, D., 2020, Digitalization, Financial Insolvency and Bankruptcy Risk Forecasting of Bulgarian Agricultural Enterprises. Scientific Papers-Series Management Economic Engeneering in Agriculture and Rural Development. 23(2), 29-35.

[4]Balina, R., Idasz-Balina, M., Achsani, N.A., 2021, Predicting Insolvency of the Construction Companies in the Credit worthiness Assessment Process-Empirical Evidence from Poland. Journal of Risk and Financial Management 14: 453. https://doi.org/10.3390/jrfm14100453

[5]Commercial Law Act, https://lex.bg/laws/ldoc/-14917630, Accessed on 10.01.2025.

[6]Dorohan-Pysarenko, L., Rębilas, R., Yehorova, O., Yasnolob, I., Kononenko, Z., 2021, Methodological Peculiarities of Probability Estimation of Bankruptcy of Agrarian Enterprises in Ukraine. Agricultural and Resource Economics: International Scientific E-Journal 7(2)

[7]European commission, 2020, Financial needs in the agriculture and agri-food sectors in Sweden. PDF www.fi-compass.eu. Accessed on 17.02.2025.

[8]Gajdosikova, D., Valaskova, K., Kliestik, T., Kovacova, M., 2023, Research on Corporate Indebtedness Determinants: A Case Study of Visegrad Group Countries. Mathematics 2023, 11, 299. https://doi.org/10.3390/math11020299;

[9]Haas, C., Radovanovich, J., 2023, The evaluation of bankruptcy prediction models based on socio-economic costs. Expert Systems with Application. 227, https://doi.org/10.1016/j.eswa.2023.120275

[10]Huo, H.Y., 2006, Bankruptcy Situation Model in Small Business: The Case of Restaurant Firms. Hospitality Review 24(2), Article 5.

[11]Kanapickienė, R., Kanapickas, T., Nečiūnas, A., 2023, Bankruptcy Prediction for Micro and Small Enterprises Using Financial, Non-Financial, Business Sector and Macroeconomic Variables: The Case of the Lithuanian Construction Sector. Risks 11, 97. https://doi.org/10.3390/ ;

[12]Kasarova, V., 2010, Models and indicators of analysis of the company's financial stability. NBU. https://eprints.nbu.bg/id/eprint/637/1/FU_1_FINAL.pdf Accessed on 3 February 2023.

[13]Kiyak, D., Labanauskaitė, D., 2012, Assessment of the Practical Application of Corporate Bankruptcy Prediction Models. Economics and Management: 2012. 17 (3)

[14]Korol, T., 2019, Dynamic bankruptcy prediction models for European enterprises. Journal of Risk and Financial Management 12: 185;

[15]Kovacova, M., Kliestik, T., 2017, Logit and Probit application for the prediction of bankruptcy in Slovak companies. Equilibrium. Quarterly Journal of Economics and Economic Policy, 12(4). 775–791. https://doi.org/10.24136/eq.v12i4.40

[16]Kuhmonen, I., Siltaoja, M., 2022, Farming on the margins: Just transition and the resilience of peripheral farms. Environmental Innovation and Societal Transitions, 43. 43-357

[17]Kulchev, K., 2023, Assessment of the Insolvency Risk of Enterprises. Economic World Collection "Tsenov "Academic Publishing House, "D.A.Tsenov" Academy of Economics - Svishtov, Bulgaria;

[18]Kulchev, K., 2023a, Key Elements of Models for Analysis of The Financial Sustainability of Enterprises. e-Journal VFU; 20; 445-452.

[19]Letyagina, E., Dadayan, E., Storozheva, A., 2020, Features and modern approaches to the analysis of the financial condition of the debtor as a necessary element of the bankruptcy procedure of agricultural enterprises. IOP Conf. Series: Earth and Environmental Science 548 (2020) 022002 IOP Publishing doi:10.1088/1755-1315/548/2/022002;

[20]Lubenova, A., 2012, Analysis of the financial condition of agricultural enterprises in Bulgaria. Nauchnitrudovena Rusenski Univwrsitet-2012, 51, 5.1.

[21]Milić, D., Tekić, D., Zekić, V., Novaković., T., Popov, M. Mihajlov, Z., 2021, Bankruptcy prediction models for large agribusiness companies in AP Vojvodina. Ekonomika poljoprivrede 68(3). 805-822.

[22]Mohammadi, S., 2016, Studying the Efficiency and the Power of Predicting Bankruptcy of Firms Listed on the Stock Exchange using Springate, Fulmer, and Zavgren Models. Mediterranean Journal of Social Sciences 7(4)4 S2.

[23]Popescu, A., 2014, Research regarding the use of discriminant analysis for assessing the bankruptcy risk of agricultural companies. Scientific Papers Series "Management, Economic Engineering in Agriculture and Rural Development". 14(4), 193-200.

[24]Prisacaru, V., Strainu, O., 2023, Implementation of the Innovative Management in the Food Industry Enterprises in the Republic Of Moldova - Current State, Barriers, Possible Solutions. Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development Vol. 23(1), 659-668.

[25]Stoyancheva, D., Angelova, R., 2024, Financial Diagnostics of Bancruptcy Risk in Agriculture. Scientific Papers Series Management, Economic Engeneering in Agriculture and Rural Development 24(2), 893 - 900.

[26]Todorov, L., 2014, Modern Business Evaluation Models. Nova Zvezda. Sofia.

[27]Valashkova, K., Durana, P., Adamko, P., Jaros, J., 2020, Financial Compass for Slovak Enterprises: Modeling Economic Stability of Agricultural Entities. MDPI Journal of Risk and Financial Management 13(5), 1-16.

[28]Valaskova, K., Gajdosikova, D., 2021, The impact of debt management on corporate earnings: Indebtedness and its effects on the financial performance of selected Visegrad group enterprises.SHS Web of Conferences 129.

[29]Yang, Z., Platt, M.H., 1999, Probabilistic Neural Networks in Bankruptcy Prediction. Journal of Business Research 44. 67-74.

[30]Zhang, F., Tadikamalla, P., Shang, J., 2016, corporate credit-risk evaluation system: integrating explicit and implicit financial performances. International Journal of Production Economics 177: 77-100.