

FORECASTING INSOLVENCY PROBABILITY THROUGH CONVENTIONAL STATISTICAL TOOLS AND ARTIFICIAL NEURAL NETWORKS: AN EMPIRICAL INVESTIGATION WITHIN ROMANIA'S AUTOMOTIVE RETAIL INDUSTRY**Ana-Maria Florentina BOBU***Stefan cel Mare University of Suceava, 729228, Romania*florentina.bobu@student.usv.ro

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Abstract

Evaluating insolvency likelihood represents a central preoccupation within financial analysis, given its profound consequences for organizational longevity and stakeholder confidence. This paper contributes to this ongoing discourse by undertaking a comparative investigation of bankruptcy prediction methodologies, specifically contrasting traditional statistical procedures against artificial neural network architectures, using empirical data drawn from Romanian passenger vehicle retailers. Our quantitative framework processes fiscal information covering the 2019–2023 period through IBM SPSS Statistics 2020, implementing both multiple linear regression and Multilayer Perceptron (MLP) neural models, with subsequent benchmarking against the classic Altman Z-Score outputs. The evidence obtained indicates that liquidity, solvency, profitability, and indebtedness ratios exert substantial influence upon insolvency probabilities, whilst neural computing techniques demonstrably enhance forecast precision. Crucially, our comparative assessment reveals that AI-based approaches do not render conventional methods obsolete but rather augment their capabilities, delivering improved sensitivity in flagging financially vulnerable entities. The practical implications of these findings extend to corporate decision-makers, capital providers, and diverse information users, who may benefit from adopting integrated analytic frameworks that harness the complementary strengths of both methodological families.

Keywords: *bankruptcy risk; artificial neural networks; multiple linear regression; economic and financial indicators; Altman model; financial forecasting.*

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INTRODUCTION

The contemporary business environment, with its hallmark characteristics of volatility, competitive intensity, and pervasive uncertainty, has elevated bankruptcy prediction to a position of strategic importance within both academic finance and professional accountancy practice. A mounting tide of corporate failures across various sectors has intensified the search for diagnostic instruments that can reliably signal incipient financial weakness, thereby empowering management teams, investors, and creditors to take preemptive corrective actions. Within this context, the convergence of traditional fiscal metrics-liquidity positions, solvency margins, profitability ratios, and leverage levels-with advanced computational techniques derived from artificial intelligence and machine learning has opened new frontiers in the development of high-accuracy predictive systems.

Notwithstanding the enduring relevance of classical financial scoring frameworks such as the Altman Z-Score, which continue to provide accessible and interpretable benchmarks for insolvency assessment, the emergence of neural network technologies has introduced the capacity to model non-linear dependencies and complex interactions among financial variables that conventional approaches may overlook. This observation motivates the central preoccupation of the present study: to determine which analytical modality-whether established statistical

procedures or contemporary AI algorithms—proves more effective in evaluating bankruptcy exposure among Romanian automotive retail enterprises. The ensuing investigation is structured around three discrete research questions:

First, we ask: what is the magnitude and direction of the influence exerted by fiscal and economic indicators upon the assessment and forecasting of insolvency danger within the automotive merchandising sector? Second, we inquire: between conventional financial scoring systems and artificial neural networks, which demonstrates superior prognostic power in evaluating bankruptcy vulnerability? Third, we explore: is there a viable role for neural network architectures as either complementary adjuncts or potentially preeminent alternatives to classical statistical methods in the construction of early-warning mechanisms for fiscal distress?

To systematically address these inquiries, the paper proceeds through several integrated sections. The opening segment establishes the theoretical landscape, exploring the conceptual foundations of insolvency, identifying its principal drivers, and elucidating the contribution of financial metrics to the evaluation of corporate stability—thereby principally engaging with the first research question. Thereafter, we survey both the established battery of traditional scoring models and the emergent family of AI-based approaches, weighing their respective merits and drawbacks, which collectively inform the response to the second question. The empirical core of the study then details our methodological apparatus, the construction of statistical and neural forecasting instruments, and the comparative analysis of derived outcomes, which together furnish the basis for addressing the third question. Finally, we synthesize our principal findings and reflect upon their theoretical and practical ramifications for the utilization of statistical and AI predictive techniques in bankruptcy risk management.

I. LITERATURE REVIEW

1.1. Assessing bankruptcy risk using economic and financial indicators and traditional models

Given the far-reaching consequences of corporate insolvency for business continuity, investment security, and creditor protection, it is hardly surprising that bankruptcy risk has attracted sustained scholarly attention within financial analysis circles. The foundational contributions in this domain, dating back to the mid-twentieth century, established that financial ratios—particularly those measuring liquidity, solvency, profitability, and indebtedness—possess considerable discriminatory power in distinguishing solvent enterprises from those approaching distress. Among these pioneering formulations, the Altman Z-Score model (Altman & Mulherin, 1998) has achieved iconic status, combining intuitive appeal with demonstrated predictive validity, and has subsequently spawned numerous industry-specific adaptations.

Recent scholarship continues to affirm the centrality of fiscal metrics in modern insolvency frameworks. In their systematic review, Billios and colleagues (2024) document that liquidity, profitability, financial autonomy, and leverage ratios feature prominently across the majority of predictive models developed over the past decade, reflecting their demonstrated sensitivity to deteriorating financial conditions. The authors nevertheless caution that model performance remains contingent upon variable selection and sectoral characteristics, implying that context-sensitive calibration is essential. This observation finds corroboration in the integrated modeling approach proposed by Issa and co-authors (2024), who demonstrate that elevated debt levels constitute a primary predictor of financial difficulty, whereas robust profitability and adequate liquidity buffers serve as protective factors that diminish insolvency likelihood. Their work further underscores the analytical benefits derived from deploying multiple indicators concurrently, thereby enhancing prognostic accuracy through the aggregation of complementary informational signals.

Despite the continued utility of classical financial rating systems, which offer straightforward application and interpretation, a growing corpus of critical scholarship has identified important limitations. Specifically, the capacity of these models to capture non-linear relationships among financial variables and to accommodate the influence of exogenous contextual factors appears constrained. This recognition has catalyzed a progressive shift in research priorities toward more flexible predictive methodologies rooted in artificial intelligence and neural computing, capable of discerning complex patterns that elude conventional techniques. The evolution toward AI-enhanced approaches provides compelling justification for undertaking a systematic comparative assessment between traditional statistical instruments and modern computational alternatives—a task to which we now turn.

1.2. Modern models for predicting bankruptcy risk: neural networks and artificial intelligence

The advent and proliferation of artificial intelligence technologies have fundamentally reconfigured the landscape of bankruptcy prediction, with emergent research increasingly oriented toward algorithmic systems that can apprehend intricate interdependencies among fiscal and economic variables (Macovei et al., 2024). Unlike conventional financial scoring mechanisms, machine learning and neural network methodologies offer the distinct advantage of simultaneous multi-variable processing and non-linear relationship detection, resulting in demonstrably enhanced predictive outcomes (Billios et al., 2024). Neural architectures, in particular, have garnered recognition as

among the most potent instruments available for insolvency forecasting, by virtue of their inherent capacity for autonomous learning, pattern recognition, and adaptation to complex data environments. These computational constructs, which draw inspiration from biological neuronal functioning, facilitate the discovery of latent configurations that conventional statistical procedures typically fail to identify.

The distinction between traditional and AI-based approaches is especially pronounced with respect to their treatment of variable relationships. Whereas multiple linear regression proceeds from the restrictive assumption of linear dependencies, neural networks accommodate non-linear associations and convoluted mutual dependencies among financial metrics with considerable facility (Billios and associates, 2024). In a complementary vein, the bibliometric investigation conducted by Grosu and co-workers (2023) documents a progressive migration of scholarly inquiry away from conventional statistical techniques and toward machine learning, artificial intelligence, and hybrid predictive architectures—a trajectory that mirrors the academic community's intensifying focus on improving prognostic precision. Their findings indicate that contemporary methodologies not only amplify predictive power but also mitigate the deleterious effects of limitations inherent in traditional financial rating systems, particularly within contexts characterized by pronounced economic volatility.

The performance of AI-based models, however, is by no means guaranteed; rather, it depends critically upon the quality of underlying data repositories and the judicious selection of variables employed during the training phase. Billios and associates (2024) observe that liquidity, profitability, financial independence, and leverage ratios continue to function as the most frequently utilized predictors even within neural network-based frameworks—the distinguishing factor being the manner in which inter-variable relationships are learned and articulated. Concurrently, the scholarly literature reveals a discernible tendency toward the construction of hybrid models that amalgamate the strengths of traditional statistical frameworks with those of AI algorithms, thereby enhancing robustness and refining decision-making capacities. This integrative impulse is particularly evident in sectors marked by pronounced financial instability.

To provide a concise overview of the principal investigative trajectories in this domain, Table 1 encapsulates the most salient scholarly contributions discerned from the specialized literature. Upon surveying these contributions, it becomes apparent that contemporary scholarship no longer construes statistical models and artificial neural networks as adversarial alternatives but rather as complementary instruments. Classical frameworks provide an interpretable and readily applicable scaffolding, whereas AI algorithms facilitate the extraction of nuanced inter-variable associations and deliver heightened predictive force within fluid economic environments. This complementarity has prompted calls for the development of integrated models that can synthesize conventional fiscal proxies alongside non-financial intelligence and modern machine learning modalities.

Table 1. Summary of the main studies on bankruptcy risk assessment using statistical models and neural networks

Author(s), year	Research objective	Methodology	Main results	Contribution of the study
Altman & Mulherin et al. (1998)	Analysis of Classical Bankruptcy Prediction Models	Theoretical analysis	Validation of the Altman model as a risk assessment tool	Theoretical foundation of modern financial scoring models
Habermann & Fischer et al. (2022)	The Relationship Between Social Performance and the Risk of Bankruptcy	Panel data regressions	Social performance influences the probability of bankruptcy depending on the context	Incorporates ESG factors into risk analysis
Kitowski et al. (2022)	Evaluation of early warning models	Empirical analysis	Classical models effectively identify vulnerable companies	Confirms the usefulness of financial scoring models
Grosu et al. (2023)	Bibliometric analysis of bankruptcy risk assessment models	Bibliometric analysis	A marked trend toward the use of artificial intelligence	Highlights current research directions
Issa et al. (2024)	Development of an integrated model for assessing bankruptcy risk	Empirical analysis	Artificial intelligence improves prediction accuracy	Supports the integration of AI algorithms into risk assessment
Billios et al. (2024)	Systematic review of financial indicators used in bankruptcy prediction	Systematic Review	Financial indicators remain the primary predictors of bankruptcy	Supports the use of hybrid models
Gao et al. (2025)	Analysis of the relationship between ESG performance and bankruptcy risk	Multivariate regressions	ESG performance reduces the probability of bankruptcy	Extends predictive models by integrating non-financial indicators

Source: Authors' compilation based on the specialized literature

A juxtapositional appraisal of the surveyed studies reveals that contemporary scholarship no longer construes statistical models and artificial neural networks as adversarial alternatives, but rather as mutually reinforcing strategies. Whereas classical frameworks provide an interpretable and readily applicable scaffolding, AI algorithms facilitate the extraction of nuanced inter-variable associations and deliver heightened predictive force within fluid economic environments.

Simultaneously, recent inquiries accentuate the exigency for devising integrated models that can synthesize conventional fiscal and economic proxies alongside non-financial intelligence and contemporary machine learning modalities.

The insights gleaned from the literature reviewed furnish partial resolution to the second investigative query (Q2), evincing that artificial neural networks constitute a high-caliber substitute for traditional financial rating systems, yet their utility remains contingent upon data integrity and the apt choice of predictor variables. These observations lend compelling justification to the execution of a comparative assessment between multiple linear regression and neural architectures, applied to Romanian automotive retail enterprises, an objective that forms the centerpiece of the empirical component of this paper.

II. RESEARCH METHODOLOGY

The overarching ambition of this investigation is to appraise insolvency vulnerability among Romanian firms operating within the passenger vehicle commercial sphere, by pitting conventional statistical frameworks against artificial neural network alternatives.

The analytical procedure is grounded in a quantitative epistemological stance, drawing upon fiscal information spanning the 2019–2024 interval, sourced from the audited financial disclosures of the enterprises constituting the sample. The dependent construct is operationalized as bankruptcy risk (BR), whilst the independent variables encompass the principal fiscal and economic metrics recurrently encountered in scholarly discourse—namely liquidity, solvency, profitability, leverage quotient, and financial self-sufficiency.

Data manipulation was executed through IBM SPSS Statistics 2020, harnessing two distinct analytical protocols: multiple linear regression, deployed to ascertain the impact of fiscal indicators upon insolvency exposure, and a Multilayer Perceptron (MLP) neural architecture, formulated to construct an AI-based prognostic instrument. The operational efficacy of both frameworks was assessed through scrutiny of statistical indices and subsequent juxtaposition of their outputs against those derived from the canonical Altman Z-Score formula. The adopted methodological configuration facilitates a direct contrast between the effectiveness of traditional constructs and contemporary AI protocols in forecasting insolvency danger, thereby assisting in the determination of the most fitting evaluative modality for the firms scrutinized.

III. RESULTS AND DISCUSSION

The cardinal objective driving this research was the evaluation of insolvency susceptibility among Romanian automotive retail enterprises, achieved through a comparative juxtaposition of the predictive capabilities manifested by traditional statistical formulations versus those exhibited by artificial neural networks. Toward this end, the investigative procedure was executed employing pertinent fiscal and economic metrics, which underwent processing within IBM SPSS Statistics 2020, leading to the concurrent development of a multiple linear regression construct alongside a Multilayer Perceptron (MLP)-based neural model.

Table 2. Correlation Matrix

		RF	RAFG	RFT	RPN	RSG	RAC
Pearson Correlation	RF	1.000	-0.587	-.134	-.365	-0.378	.312
	RAFG	-.587	1.000	.504	.397	.809	-.144
	RFT	-0.134	.504	1.000	.179	.623	.259
	RPN	-.365	.397	.179	1.000	.245	.273
		RF	RAFG	RFT	RPN	RSG	RAC
	RSG	-.378	.809	.623	.245	1.000	-.090
Sig. (1-tailed)	RAC	.312	-0.144	.259	.273	-0.090	1.000
	RF		.000	.073	.000	.000	.000
	RAFG	.000		.000	.000	.000	.059
	RFT	.073	.000		.026	.000	.002
	RPN	.000	.000	.026		.004	.001
	RSG	.000	.000	.000	.004		.166
N	RAC	.000	.059	.002	.001	.166	
	RF	119*	119	119	119	119	119
	RAFG	119	119	119	119	119	119
	RFT	119	119	119	119	119	119

	RPN	119	119	119	119	119	119
	RSG	119	119	119	119	119	119
	RAC	119	119	119	119	119	119

*The sample consists of 20 firms $\times$ 6 years (2019–2024) = 120 observations. One observation was excluded due to missing data, resulting in $N = 119$ for the regression analysis

Source: Author's own analysis in SPSS 2020

The preliminary analysis revealed the existence of significant relationships among the economic and financial variables included in the study. The results presented in *Table 2* indicate that liquidity, solvency, and financial autonomy indicators are negatively correlated with the risk of bankruptcy, while the debt ratio has a positive influence on the probability of financial difficulties. These results confirm the conclusions drawn in the literature, according to which the deterioration of financial stability is primarily driven by rising debt and a decline in firms' ability to pay.

Table 3. Summary of the model

Model	R	R-Square	Adjusted R-Square	Standard Error of the Estimate	Durbin-Watson
1	.685 ^a	.469	.446	.321	1.286

a. Predictors: (Constant), RAC, RSG, RPN, RFT, RAFG

b. Dependent Variable: RF

Source: Author's own analysis in SPSS 2020

The results in *Table 3* highlight the high explanatory power of the regression model, with the coefficient of determination (R^2) indicating that a significant proportion of the variation in bankruptcy risk is explained by the economic and financial indicators included in the analysis. These results confirm the model's suitability and justify its use in assessing the relationship between the analyzed variables.

Table 4. ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10.296	5	2.059	19.996	.000 ^b
	Residual	11.637	113	.103		
	Total	21.933	118			

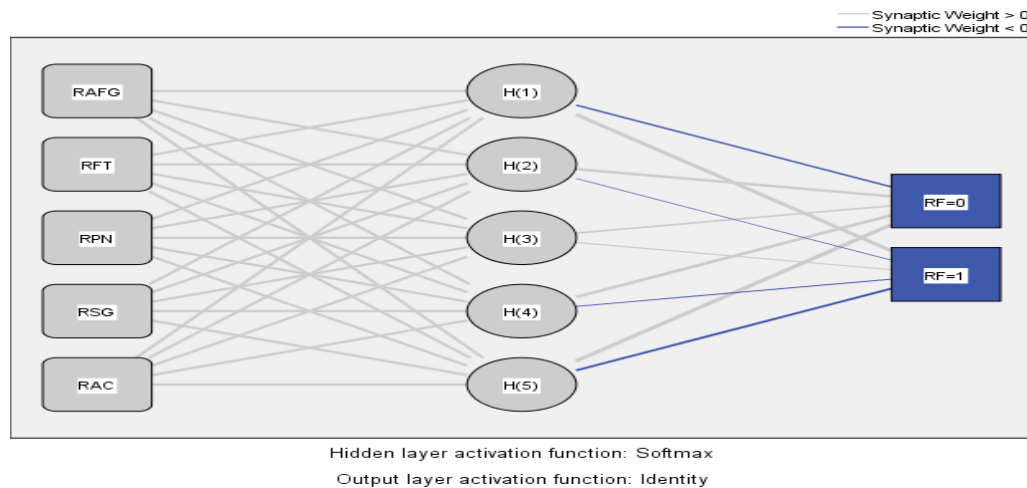
a. Dependent Variable: RF

b. Predictors: (Constant), RAC, RSG, RPN, RFT, RAFG

Source: Author's own analysis in SPSS 2020

The results of the ANOVA test in *Table 4* confirm the statistical significance of the regression model; the significance threshold (Sig. < 0.05) indicates the existence of a significant relationship between the independent variables and the risk of bankruptcy. Therefore, the constructed model can be considered valid for explaining the analyzed phenomenon.

The results of the multiple linear regression model, presented in the table above, confirm the statistical validity of the econometric model, with the ANOVA test indicating the existence of a significant relationship between the independent variables and the risk of bankruptcy. At the same time, the coefficient of determination demonstrates that the model explains a high proportion of the variation in the dependent variable, which confirms the relevance of the economic and financial indicators used in the prediction process. An analysis of the regression coefficients reveals that the debt ratio has a positive influence on the risk of bankruptcy, while liquidity, solvency, and profitability help reduce the probability of financial difficulties. In light of these considerations, *Figure 1* illustrates the architecture of the neural network used in this study as follows:

**Figure 1.** Neural network for bankruptcy risk

Source: Author's own analysis in SPSS 2020

To improve predictive performance, a model based on artificial neural networks was developed. Figure 1 presents the architecture of the neural network model used in this study, built on the Multilayer Perceptron algorithm. The model allowed for the identification of the relative importance of each independent variable, with the results indicating that net profitability, debt ratio, financial autonomy, and liquidity are among the most important predictors of bankruptcy risk. The classification performed by the neural network demonstrates a high ability to identify companies in financial distress, confirming the usefulness of artificial intelligence algorithms in analyzing the complex relationships among economic and financial indicators.

IV. CONCLUSIONS

The central ambition animating this scholarly endeavor was the appraisal of insolvency danger confronting Romanian enterprises in the passenger vehicle distribution sector, accomplished through a head-to-head comparison of the operational proficiency exhibited by conventional statistical schemas versus artificial neural network systems.

The empirical outcomes corroborate that fiscal and economic proxies constitute pivotal determinants in the recognition of monetary adversities, and their incorporation within prognostic architectures serves to amplify the exactitude of insolvency risk evaluation. The side-by-side assessment underscores that while classical financial rating instruments—the Altman formulation being a quintessential instance—retain their value by virtue of straightforwardness and interpretive facility, neural network-based constructs deliver augmented capabilities in detecting convoluted interrelations among fiscal attributes and in stratifying enterprises according to their insolvency exposure tiers.

These findings are thoroughly consonant with emergent tendencies delineated within scholarly literature concerning the deployment of AI methodologies in financial scrutiny. The primary scholarly value-added of this investigation resides in the applied juxtaposition of conventional frameworks against AI algorithms upon a Romanian automotive retail sample, evincing that their synergistic utilization can engender more efficacious early-alert mechanisms and facilitate more judicious administrative and capital allocation determinations. As is characteristic of any scientific undertaking, the present inquiry is not immune to certain constraints. The analytical scope was confined to a solitary industrial domain and circumscribed within a relatively abbreviated temporal horizon—factors that may curtail the generalizability of findings to alternative economic spheres. Moreover, the constructed models were predominantly predicated upon fiscal and economic proxies, without the systematic infusion of macroeconomic determinants or non-financial parameters.

In light of these acknowledged limitations, subsequent scholarly endeavors might profitably broaden the analytical aperture through the inclusion of more expansive samples, diversified industrial sectors, and extended observational windows. Additionally, the incorporation of ESG metrics, macroeconomic variables, and alternative AI algorithms—including Random Forest, Support Vector Machine, or deep learning paradigms—could materially contribute to the articulation of more resilient prognostic frameworks that are better calibrated to contemporary economic realities.

In summation, this investigation foregrounds that the integrated employment of statistical constructs alongside artificial neural networks constitutes a propitious trajectory for insolvency evaluation, furnishing a more

adaptable and efficacious *modus operandi* relative to the exclusive deployment of traditional methodologies. The insights generated through this study may function as a valuable repository of knowledge for both academic researchers and practicing professionals engaged in financial performance assessment and risk mitigation activities.

REFERENCES

1. Abdul Rahman, A. M., & AbdulRahman, B. S. (2025). The role of financial ratios in bankruptcy prediction: An empirical study using contemporary financial data. *Journal of Accounting and Finance Research*, 3(2), 43–55.
2. Almeida Gomes, L. (2023). Risk and bankruptcy research: Mapping the state of the art. *Journal of Risk and Financial Management*, 16(8), 361.
3. Altman, E. I. (1968). Financial ratios, discriminant analysis, and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589–609.
4. Altman, E. I., & Mulherin, J. H. (1998). Corporate financial distress: A review of the literature. *The Journal of Finance*, 53(6), 1857–1892.
5. Anghel, I., & Enache, C. (2020). Macroeconomic determinants of corporate failures: Evidence from Romania and Spain. *Journal of Business Economics and Management*, 942–944.
6. Arumsari, A. R. A., Jubery, M., & Fajarisman, B. (2025). Analyzing the prediction of a company's bankruptcy using the Springate method and the Altman method. *Indonesia Sosial Sains Journal*, 6(9), 2955–2962.
7. Bas, E., & Egrioglu, E. (2025). A new automatic forecasting method based on an explainable deep dendritic artificial neural network. *Scientific Reports*.
8. Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 4, 71–111.
9. Beaver, W. H., Cascino, S., Correia, M., & McNichols, M. F. (2024). Bankruptcy in groups. *Review of Accounting Studies*, 29(4), 3449–3496.
10. Billios, D., & Seretidou, D. (2024). The power of numerical indicators in predicting bankruptcy: A systematic review. *Journal of Risk and Financial Management*.
11. Chelba, A.-A., & Ciobotariu, I.-Ş. (2025). Non-financial information: An important source of information in decision-making in Romanian companies. *Studies and Scientific Researches. Economics Edition*, 49–60.
12. Chiosea, D.-B., & Hăţegan, C.-D. (2024). Research trends in going concern assessment and financial distress over the past two decades: A bibliometric analysis. *Risks*, 12(12), 184.
13. Dwivinna, N., Dewi, W., & Murhadi, B. S. (2023). Financial ratios, corporate governance, and macroeconomic indicators in predicting financial distress. *Journal of Law and Sustainable Development*.
14. Gao, B., Liu, H., Tong, S., & Jin, Y. (2025). Does ESG performance reduce bankruptcy risk? *International Journal of Financial Studies*, 13(4), 221.
15. Grosu, V., & Chelba, A. A. (2020). Bankruptcy risk: Concepts and approaches in the economic literature. *European Journal of Accounting, Finance & Business*, 8(3). <https://www.accounting-management.ro/index.php?pag=showarticle&issue=24&year=2020&brief=2415>
16. Grosu, V., Chelba, A.-A., Melega, A., Botez, D., & Socoliuc, M. I. (2023). Bibliometric analysis of the specialized literature on bankruptcy risk assessment models. *Strategic Management – International Journal of Strategic Management and Decision Support Systems in Strategic Management*, 28(2).
17. Hlaciuc, E. (2024). Research on the bankruptcy risk of Romanian insurance companies based on financial indicators from financial statements. *European Journal of Accounting, Finance & Business*.
18. Macovei, A. G., Popelo, O., Zhavoronok, A., Dankiewicz, R., Cosmulese, C. G., & Popova, L. (2024). Pre-and post-effect of COVID-19 on the insurance industry: A study based on Romanian companies. 15(2), 74-84. doi:10.21511/ins.15(2).2024.07
19. Nagy, C. M., Ghica, E. D., & Tipărescu, C.-A. (2023). Theoretical concepts regarding bankruptcy risk. In *Human Rights in the Light of National Case Law* (pp. 306–319).
20. Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 18(1), 109–131.
21. Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business*, 74(1), 101–124.
22. Sun, J., Li, H., Huang, Q., & He, K. (2014). Predicting financial distress using support vector machines and neural networks. *Expert Systems with Applications*, 41(4), 1278–1286.
23. Zhang, G., Hu, M. Y., Patuwo, B. E., & Indro, D. C. (1999). Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis. *European Journal of Operational Research*, 116(1), 16–32.