

DOI: [https://doi.org/10.30970/fp.2\(60\).2026.198206207](https://doi.org/10.30970/fp.2(60).2026.198206207)

JEL Classification: G21, G32, O33, C53

DIGITAL TOOLS FOR ASSESSING THE CREDITABILITY OF ENTERPRISES

SMOLINSKA Sofia

PhD in Economics, Associate Professor,
Associate Professor of the Department of Financial Management
Ivan Franko National University of Lviv
ORCID ID: <https://orcid.org/0000-0002-7355-6988>

SMOLINSKYY Valentyn

PhD in Economics, Associate Professor,
Associate Professor of the Department of Information Technologies
Stepan Gzhytskyi Lviv National University of Veterinary Medicine and Biotechnologies
ORCID ID: <https://orcid.org/0000-0002-5482-8263>

Abstract. *The article examines modern digital tools for assessing enterprise creditworthiness. An original six-group classification of these tools is proposed. A comparative analysis of traditional and digital approaches is carried out, and the advantages of ensemble machine learning methods are substantiated.*

Keywords: *creditworthiness; digital tools; machine learning; credit scoring; financial technologies; big data; alternative data.*

The article examines the transformation of approaches to assessing the creditworthiness of enterprises in the context of the digitalization of the financial sector. It summarizes theoretical and applied approaches to credit scoring, identifies the limitations of classical methods, in particular their retrospective nature, subjectivity of assessment, and insufficient consideration of non-financial risk factors. It is proven that the implementation of machine learning technologies, big data, API integrations, RegTech solutions, blockchain technologies, and alternative data platforms provides increased accuracy, speed, and scalability of credit analysis.

The purpose of the study is to systematize and classify modern digital tools for assessing creditworthiness, conduct a comparative analysis of their effectiveness relative to traditional methods.

The results of the study indicate that ensemble machine learning algorithms demonstrate the highest predictive accuracy, surpassing traditional statistical models. At the same time, it was found that logistic regression retains its value in the context of regulatory transparency and interpretability of decisions. A comparative characteristic of traditional and digital approaches is proposed, which confirms the advantages of digital technologies in data processing speed, automation and the ability to analyze new enterprises without a credit history.

The scientific novelty lies in the development of a generalized classification of digital tools for assessing the creditworthiness of enterprises and the construction of a four-level conceptual model of an integrated credit analysis system that combines the stages of data

collection, processing, modeling and formation of a substantiated credit decision with elements of algorithm explainability.

The scope of application of the results covers banking institutions, financial companies, the FinTech sector and regulatory authorities that carry out credit risk assessment and implement digital scoring technologies.

The conclusions confirm the feasibility of transitioning to hybrid credit analysis models that combine algorithmic digital tools and expert assessment. Further development of the research is associated with the adaptation of the models to the Ukrainian market, increasing their interpretability and improving the regulatory support for algorithmic credit scoring.

Reference

1. Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model. *Journal of International Financial Management & Accounting*, 28(2), 131–171.
2. Addo, P. M., Guegan, D., & Hassani, B. (2018). Credit Risk Analysis Using Machine and Deep Learning Models. *Risks*, 6(2), 38.
3. Barboza, F., Kimura, H., & Altman, E. (2017). Machine Learning Models and Bankruptcy Prediction. *Expert Systems with Applications*, 83, 405–417.
4. Lessmann, S., Baesens, B., Seow, H.-V., & Thomas, L. C. (2015). Benchmarking State-of-the-Art Classification Algorithms for Credit Scoring: An Update of Research. *European Journal of Operational Research*, 247(1), 124–136.
5. Dastile, X., Celik, T., & Potsane, M. (2020). Statistical and Machine Learning Models in Credit Scoring: A Systematic Literature Survey. *Applied Soft Computing*, 91, Article 106263.
6. Bussmann, N., Giudici, P., Marinelli, D., & Papenbrock, J. (2021). Explainable Machine Learning in Credit Risk Management. *Computational Economics*, 57, 203–216.
7. Dumitrescu, E., Hué, S., Hurlin, C., & Tokpavi, S. (2022). Machine Learning for Credit Scoring: Improving Logistic Regression with Non-linear Decision-tree Effects. *European Journal of Operational Research*, 297(3), 1178–1192.
8. Bücker, M., Szepannek, G., Gosiewska, A., & Biecek, P. (2021). Transparency, Auditability, and Explainability of Machine Learning Models in Credit Scoring. *Journal of the Operational Research Society*, 73(1), 70–90.
9. Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). ACM.
10. Leo, M., Sharma, S., & Maddulety, K. (2019). Machine Learning in Banking Risk Management: A Literature Review. *Risks*, 7(1), 29.
11. Basel Committee on Banking Supervision. (2018). *Sound Practices: Implications of Fintech Developments for Banks and Bank Supervisors*. BIS.
12. European Banking Authority. (2020). *EBA Report on Big Data and Advanced Analytics* (EBA/REP/2020/01). EBA.
13. National Bank of Ukraine. (2016). *Resolution No. 351 on Determining Credit Risk by Ukrainian Banks (30.06.2016)*. <https://zakon.rada.gov.ua/laws/show/v0351500-16>

Дата надходження статті: 08.05.2026

Дата прийняття статті: 19.05.2026

Дата публікації статті: 31.05.2026