INNOVATIVE APPROACHES TO RISK MANAGEMENT IN STARTUP FINANCING

Butenko O., *Ph.D. in Economics,* ***Levkoveț̦s O.,*** *Ph.D. in Economics, Semen Kuznets Kharkiv National University of Economics*

In conditions of limited capital, reduced investment activity, and increasing risks, startups need innovative financial management approaches. Digital technologies, including big data analytics, blockchain, and artificial intelligence, provide new opportunities for assessing, forecasting, and mitigating financing risks. Studying innovative risk management models helps develop effective strategies for startups to adapt to turbulent economies, which is especially important for Ukraine's recovery and modernization. Traditional methods based on financial ratios and expert evaluations are becoming less sufficient amid market volatility and rapid technological change. Therefore, modern risk forecasting models that incorporate machine learning, deep data analysis, and digital visualization are essential. These models evaluate risk levels in startup investments and help optimize investment strategies. Classical statistical methods -such as econometric modeling, regression, variance, discriminant, and cluster analyses—remain the foundation for digital models, ensuring transparency and interpretability. Logistic regression helps estimate default probability, while time series models (ARIMA, GARCH) project fluctuations in investment flow.

Research on such statistical tools is detailed in the work of Altman, E. [1], where he developed the Z-score model for bankruptcy prediction, as well as in modern sources such as Jorion, P. "Value at Risk: The New Benchmark for Managing Financial Risk" [2] and Brooks, C. "Introductory Econometrics for Finance" [3], which highlights the evolution of quantitative risk analysis methods in finance. Thus, classical statistical approaches lay the theoretical foundation for further analysis of the latest risk forecasting models using digital analytical platforms, Big Data, and artificial intelligence.

Ensemble machine learning methods are among the most powerful tools for current investment risk forecasting, as they combine several weaker models into a robust predictive mechanism, enabling the detection of complex relationships between financial, behavioral, and market features of startups. The Random Forest method provides stability and reduces overfitting through the random selection of data and feature subsets, making it a useful baseline ensemble for risk classification [4].

Gradient boosting, as described in the classic works of Friedman and in modern implementations such as XGBoost, LightGBM, and CatBoost, sequentially corrects the errors of previous models and often provides better accuracy in tasks with many variables and complex, nonlinear dependencies. In practice, ensemble models combined with active feature engineering are used for risk prediction in startups. These ensembles have high performance in such cases but require careful hyperparameter tuning, significant computational resources, and mechanisms for their interpretation.

Since the financial environment, especially during wartime and post-war transformations, changes over time, an important component of the workflow is monitoring the stability of models and periodically retraining or recalibrating them. Research on adaptation to changes shows a set of algorithms and practices for automatically detecting and adapting models to new conditions. To ensure transparency in decision-making within the financial sector, methods such as Explainable AI (SHAP, LIME) are employed, which explain the role of features in specific predictions of ensemble models. This is crucial for maintaining investor trust and ensuring regulatory compliance.

Thus, ensemble ML algorithms (Random Forest, Boost, LightGBM, CatBoost), combined with high-quality data processing, time-based validation, concept drift monitoring, and XAI, constitute a justified and competitive approach to modern prognostics of investment risks in startups [4]. As shown in Table 1, approaches to risk forecasting in startup investments encompass a wide range of methods – from classical statistical models to deep learning and graph networks. Their combined use allows for increased accuracy in assessment, ensures interpretability of results, and adapts to the rapidly changing conditions of the wartime and post-war economy.

Table 1 – Main approaches to investment risk forecasting in startups under digital transformation conditions

Approach Type	Method / Model	Digital Tools	Advantages	Limitations
Classical Statistical Methods	Logistic Regression, Discriminant Analysis, ARIMA	Excel, SPSS, Stata	Ease of interpretation, transparency of models and effectiveness with small samples	Do not account for nonlinear relationships, low accuracy in complex environments
Ensemble ML Algorithms	Random Forest, Gradient Boosting, XGBoost	Python (Scikit-learn, XGBoost), RapidMiner	High accuracy, robustness to overfitting and automatic feature selection	Require large datasets, less interpretability
Deep Learning	LSTM, GRU, CNN	TensorFlow, PyTorch	Modeling of temporal and behavioral patterns, self-adaptation ability	High computational costs, 'black box'
Graph Neural Networks (GNN)	GraphSAGE, GCN	DGL, PyTorch Geometric	Network risk analysis and relationships between investors and partners	Complexity of constructing graph structures, requiring large datasets
Explainable AI (XAI)	SHAP, LIME	Python (SHAP, LIME packages)	Model transparency, increased investor trust, and regulatory compliance	Does not always explain complex neural network architectures

Overall, the review of ensemble algorithms shows that complex temporal and behavioral patterns characteristic of financial flows and startup activity require the use of deep learning methods. Risks associated with the network of connections between investors, partners, and counterparties are better modeled using graph neural networks. Effective application of these approaches depends on high-quality data, Explainable AI for decision transparency, regular model monitoring (to control concept drift), and scenario analysis for stress testing forecasts. The analysis suggests that modern methods for assessing investment risks in startups are undergoing significant evolution due to digitalization in the financial sector. Classical statistical techniques, such as logistic regression, discriminant analysis, and time series models, remain useful for basic assessments, but their predictive power is limited in the high-dynamic, nonlinear environment of startup investments. Meanwhile, modern ensemble machine learning approaches, such as Random Forest, Gradient Boosting, and XGBoost, demonstrate a substantial increase in efficiency, allowing for the combination of different features and mitigating overfitting risks through multi-layered model structures. Deep learning models, particularly LSTM and GRU, play a crucial role in capturing nonlinear relationships and dependencies in financial flows, facilitating the modeling of complex temporal and behavioral patterns in startups. These architectures are particularly valuable for analyzing dynamic investment risks. Graph neural networks facilitate the analysis of network effects within the startup ecosystem, emphasizing connections between investors, partners, and market segments that influence potential chain risks.

At the same time, the reliability of forecast results depends on the quality of data, the availability of Explainable AI (XAI) for model interpretation, and regular scenario analysis to adapt to changing macroeconomic conditions. Methods of explainable artificial intelligence, such as SHAP and LIME, provide transparency in decision-making, which is important for financial regulation and investor trust. In summary, digital analytical tools combined with machine learning and deep data analysis methods create a new approach to risk management in startup financing. They not only help improve forecast accuracy but also ensure the adaptability and resilience of financial decisions during wartime and post-war turbulence. Future research should focus on developing hybrid models that combine statistical and neural approaches, as well as creating integrated platforms for automated risk control that consider ESG factors and behavioral economics.

List of References:

1. Altman, E. I. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance*. 1968. Vol. 23, No. 4, pp. 589-609. DOI:10.1111/j.1540-6261.1968.tb00843.x. URL: onlinelibrary.wiley.com+1

2. Jorion, P. Value at Risk: The New Benchmark for Managing Financial Risk. 2nd ed. New York: McGraw-Hill, 2007. ISBN 0071228314. amazon.co.uk+1

3. Brooks, C. Introductory Econometrics for Finance. 2nd ed. Harlow: *Pearson Education Limited*, 2019. URL: https://new.mmf.lnu.edu.ua/wp-content/uploads/2018/03/brooks_econometr_finance_2nd.pdf

4. Breiman L. Random forests / L. Breiman // *Machine Learning*. 2001. Vol. 45, № 1. P. 5–32. URL:https://link.springer.com/article/10.1023/A%3A1010933404324

5. Friedman J. H. Greedy function approximation: a gradient boosting machine. *The Annals of Statistics*. 2001. Vol. 29, № 5. P. 1189–1232. URL: https://jerryfriedman.su.domains/ftp/trebst.pdf.

FEATURES OF ANALYSING FINANCIAL AND CREDIT RISKS IN FOREIGN ECONOMIC ACTIVITY OF SMALL ENTERPRISES UNDER MARTIAL LAW

Grygoriy Stadnyk, *PhD in Economics, Professor,* ***Yuliia Sytnikova,*** *master, O. M. Beketov National University of Urban Economy in Kharkiv*

In the current conditions of martial law in Ukraine, foreign economic activity of enterprises is becoming particularly important, as it remains a source of foreign currency earnings and a means of securing strategic raw materials and resources.