The object of this study is to predict the rationality of financial decisions in the context of digitalization of financial markets. In the context of digitalization of financial markets, about ¼ of financial decisions turn out to be irrational for financial market participants. Under these conditions, the problem is the inability of financial market participants to predict the rationality of financial decisions.

The devised multi-vector model for predicting the rationality of financial decisions in the context of digitalization of financial markets makes it possible to evaluate key indicators of decision-making efficiency and minimize risks. It was found that the use of the adaptive Adam optimization algorithm provides a reduction in the average forecasting error by 18.7 % compared to conventional methods, such as gradient descent. The use of a utility function with a correction parameter β made it possible to smooth out market fluctuations, reducing the deviation of predicted values from actual values by an average of 12.3 %. The conducted scenario modeling using the Monte Carlo method demonstrated that under conditions of high market volatility, the accuracy of forecasts remains stable and exceeds 85 %. Testing the model on the example of five Ukrainian financial companies (Moneyveo, LeoGaming Pay, Ukrfinzhytlo, European Microfinance Alliance, Smart Pay) over the period 2018–2023 showed that the level of irrational financial decisions decreased on average from 24.6 % to 15.2 %, which is equivalent to saving financial resources in the amount of UAH 37.8 million per company. This indicates the significant potential of the model in improving the quality of financial management and ensuring sustainable development of financial markets.

The practical value of the devised multi-vector predictive model of financial decisions rationality relates to its ability to optimize the process of assessing risks and investment returns, taking into account the multifactorial nature of the modern market environment. The results could become a tool for strategic planning and assessing investment attractiveness

Keywords: multi-vector forecasting model, digitalization of financial markets, financial management, finance, risks

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CONSTRUCTION OF A MODEL FOR FORECASTING THE RATIONALITY OF FINANCIAL DECISIONS UNDER THE CONDITIONS OF FINANCIAL MARKETS DIGITALIZATION

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1. Introduction

In today's digitalized financial markets, accompanied by the active implementation of digital technologies such as artificial intelligence, machine learning, and big data analysis, the paradigm of the functioning of the financial system is changing significantly. This contributes to the integration of markets, increasing the speed of information flows, and the availability of financial tools for a wide range of participants. At the same time, the complexity of market risk analysis is increasing, which increases the likelihood of making irrational financial decisions that can lead to significant capital losses. In the period from 2020 to 2024, the complexity of market risk analysis caused significant financial losses due to irrational decisions. In particular, in 2023, the French energy company EDF suffered losses of almost 0.5 billion euros due to unsuccessful operations in energy markets during sharp price fluctuations. The ongoing Russian-Ukrainian war has led to significant economic losses. As of October 2024, indirect financial losses to the economy exceeded USD 1.2 trillion. The largest losses were recorded in trade (over USD 400 billion), industry, including construction and services (USD 409.9 billion), and agriculture (almost USD 100 billion). In addition, the share of non-performing loans to individuals in Ukraine increased from 16.86 % at the beginning of the war to 32.4 % at the beginning of February 2023, indicating a deterioration in the quality of banks' loan portfolios. These examples demonstrate that the complexity of market risk analysis and underestimation of potential threats could lead to significant financial losses both at the international and national levels. Therefore, effective risk management and in-depth analysis of financial tools are critically important to prevent similar situations in the future. The COVID-19 pandemic has significantly impacted the digital economy, accelerating its transformation. In 2020, e-commerce grew by 34 %, exceeding expectations and reaching levels not predicted until 2025. The pandemic has also contributed to changing consumer behavior, increasing demand for online services and goods, and by 2025, 95 % of all purchases are expected to be made online. The high concentration of activity in e-commerce markets highlights the scale and importance of this sector to the global economy. Investment in the latest technologies is also increasing. For example, it is predicted that by 2030, global augmented reality markets will reach a capitalization of USD 38.6 billion, demonstrating an annual growth rate of 35 %. This creates a need to build models that can take into account the multifactorial nature of the market environment, adapt to changing conditions, and ensure forecasting accuracy. The question arises of integrating innovative approaches to modeling the rationality of financial decisions, which involves the use of adaptive algorithms, scenario modeling, and tools for risk reduction.

The relevance of the problem relates to the fact that under the conditions of digitalization, as well as under the influence of the COVID-19 pandemic and war, a significant proportion of financial decisions turn out to be irrational. Financial losses are increasing against the background of the acceleration of the digital transformation of financial markets. Therefore, research aimed at identifying factors that influence the rationality of financial decisions and predicting the rationality of these decisions is relevant.

2. Literature review and problem statement

In the process of forming a model for predicting the rationality of financial decisions in the context of digitalization of financial markets, it is necessary to take into account many theoretical and practical aspects. In [1], the results of research that became the basis of the theory of efficient capital markets are reported. It is shown that markets are efficient if asset prices fully reflect available information. However, issues related to the analysis of market anomalies and behavioral factors remain unresolved, which limits the possibilities of accurate forecasting. In addition, in [2], the theory of rational option pricing is proposed, which is fundamental for the evaluation of financial derivatives, but leaves open the issues of modeling accuracy under conditions of high volatility. This emphasizes the importance of taking into account additional variables to improve the adaptability of models. In [3], time series analysis methods for forecasting are proposed, which have proven effective for assessing short-term trends. However, in the cases of high uncertainty, classical approaches are insufficient. The need for hybrid models is confirmed in study [4], which emphasizes the integration of machine learning into such systems, although the authors do not specify the integration mechanism. Paper [5] considers prospect theory and shows how risk and loss perception affect decision-making but does not provide specifics for predicting the results of these decisions. These results emphasize the need to take into account psychological aspects in modeling, which is also confirmed in work [6], which analyzes cognitive factors and their impact on investment decisions but does not take into account risk factors. Brand equity management, analyzed in [7], demonstrates the potential for using combined approaches that take into account financial and non-financial factors. This is consistent with the approach described in [8], which proposes a system of balanced indicators for translating strategies into action. However, these papers lack a forecast of the capitalization of strategic decisions. Adapting these models to the specificity of small enterprises requires further research. In [9], irrational behavior in markets is analyzed, which leads to bubbles and crises, but the author considers the connection between irrational behavior and the action of objective factors rather superficially. This limits the practical significance of this approach. The same applies to study [10], which examines the impact of low-probability events, known as “black swans”, on financial systems. Both studies emphasize the need to construct models that can take into account unpredictable factors that are both subjective and objective. Work [11] considers the impact of market transparency on the quality of trade. It is shown that increasing transparency helps reduce information asymmetry, but questions remain about the impact of transparency on data confidentiality. Study [12] proposes scenario modeling for the strategic management of the market value of banks. This approach effectively takes into account various scenarios of economic development but requires adaptation to the conditions of rapid market changes. Paper [13] proposes a “random forests” method for machine learning, which is effective for classification and regression. However, its computational complexity remains a problem, which is also relevant for the application of an adaptive approach to modeling, as noted in [14]. In [15], an algorithm for adapting directions for real-time optimization is considered, which makes it possible to increase the efficiency of processes. However, the issue of scaling to complex systems requires further research. In [16], the adaptation of constraints for process optimization is analyzed, which makes it possible to improve the efficiency of management of complex systems; however, the authors did not take into account the influence of random factors on the state of systems and the dynamics of their development. Study [17] focuses on modifying the output parameters for real optimization, which makes it possible to significantly increase the accuracy and efficiency of processes, however, the researchers overlooked the probability of combining business processes, which leads to the emergence of additional criteria for evaluating input data and their correlation with the results obtained. Paper [18] proposes a dual approach to modifying parameters to increase the adaptability of models under real conditions. Despite this, the authors ignored the information noise factor, which should be taken into account when combining parameters. In this context, work [19] considers the use of neural networks for dynamic optimization, which demonstrates high accuracy under complex conditions. However, the computational cost of this approach could be a significant limitation. Study [20] complements these approaches by considering simulation modeling for improving mentoring programs. However, the authors did not take into account the impact of causal relationships between indirect factors on the performance indicators of simulation modeling. In turn, work [21] analyzes the information-reflexive approach to managing the development of mentoring systems, which makes it possible to increase the efficiency of training and personnel management, but only in the absence of scaling of business processes since the authors did not take into account the interaction of the coefficients of change in managerial productivity with the values of capitalization of the intellectual potential of mentors. Study [20] focuses on the application of digital approaches to mentoring management in corporate environments, which opens up new horizons for the methods of transferring skills and knowledge but does not answer the question of how to avoid uncontrolled leakage of information to competitors under the conditions of using digital approaches. Paper [22] considers the development of a customer service system in e-commerce. It is shown that the use of the latest technologies makes it possible to increase the level of customer satisfaction, but the issue of integrating these systems into small businesses remains. Work [23] analyzes the impact of financial technologies on the efficiency of banking activities, it is noted that fintech significantly improves productivity. However, the issue of regulation remains relevant. Paper [24] highlights the potential of machine learning for risk assessment, but the complexity of the algorithms poses challenges for their implementation. A review of machine learning methods for financial risk management in [25] shows that these approaches reduce risks but their adaptation to global financial systems requires further research. Study [26] analyzes the use of artificial intelligence in financial trading, which increases efficiency but raises ethical questions. Paper [27] examines methods for forecasting stock markets based on historical data. This approach demonstrates the potential for making informed investment decisions but the accuracy of forecasts under conditions of high volatility remains limited. Study [28] analyzes the impact of digital transformation on the financial sustainability of companies, and [29] – the impact on production efficiency, emphasizing the need to devise balanced innovation strategies. However, the authors of those studies have neglected the parameters characterizing the impact of digital transformation on the competitiveness of enterprises. Paper [30] examines the impact of policy on the digital transformation capability of agricultural enterprises in Vietnam, emphasizing the importance of the accessibility of policy decisions, but the authors did not propose a specific method for assessing such an impact, which limits the possibilities of assessing the impact of policy on the digital transformation capability. In [31], the role of artificial intelligence in financial trading is investigated, where ethical issues are a critical aspect, but there are no methodological recommendations for quantitative or qualitative assessment of the impact of factor indicators on performance indicators. Work [32] analyzes the use of big data for making management decisions but data security issues require additional measures. In general, our review of the literature demonstrates a high potential for forming a model to predict the rationality of financial decisions. However, there are a significant number of unresolved issues that require additional research and integration of modern digital technologies to increase the accuracy, adaptability, and efficiency of financial models.

3. The aim and objectives of the study

The purpose of our study is to build a multi-vector predictive model of the rationality of financial decisions in the context of digitalization of financial markets, which could allow various stakeholders to improve the efficiency of financial management.

To achieve this goal, a number of tasks were performed, namely:

– to propose the main components of the multi-vector predictive model of the rationality of financial decisions;

– to perform adaptive tuning and testing of the multi-vector model of the rationality of financial decisions using the example of several financial companies.

4. The study materials and methods

The object of our study is to predict the rationality of financial decisions in the context of digitalization of financial markets.

The hypothesis of the study assumes that the practical application of the devised multi-vector predictive model, which would optimize the process of assessing risks and investment returns, taking into account the multifactorial nature of the modern market environment, could make it possible to reduce the share of irrational financial decisions.

Before starting the study, the following assumptions were accepted:

– the rationality of financial decisions depends on a number of factors, such as transparency, efficiency, risk management effectiveness, adaptability, innovation, and external factors (economic conditions, market volatility);

– adaptive adjustment of the model parameters based on the Adam algorithm will make it possible to increase its accuracy in accordance with market changes;

– the use of the Monte Carlo method will make it possible to evaluate various scenarios of the market situation;

– introduction of a utility function with a correction parameter will contribute to the normalization of features, taking into account the instability of market conditions;

– the multi-vector model will be effective for assessing risks and returns on investments in digital financial markets.

The following simplifications were adopted in the research process:

– the Adam algorithm was used to dynamically adjust the weighting coefficients without taking into account alternative optimization methods;

– the analysis of financial decisions was carried out on the example of a limited sample of companies operating in highly digitized financial markets;

– the influence of psychological and behavioral factors of decision-making in the financial sector was not taken into account;

– the utility function for normalizing features provides a simplified approach to determining the correction parameter β;

– scenario modeling was carried out using a limited number of scenarios that do not take into account all possible options for market dynamics;

– the possible long-term effects of the decisions made were not considered since the research is focused on short- and medium-term forecasting.

To determine the main features and external factors, an analysis of key characteristics of market conditions was used, which made it possible to identify important indicators that influence decision-making. In order to establish weight coefficients for the model components, the adaptive Adam algorithm was used, which provided dynamic adjustment of weight coefficients in accordance with changes in market conditions. A nonlinear utility function was constructed for each feature with a correction parameter, which makes it possible to normalize the values of the features in the range [0; 1]. That made it possible to take into account market conditions and ensure adaptability, reducing sensitivity to market fluctuations. To construct an integral indicator of rationality, a nonlinear combination of features was used, which takes into account the weights of features and external factors, as well as the interdependence between them. For scenario modeling under different market conditions, the Monte Carlo method was used, which made it possible to generate different scenarios of the market situation, adapting the weights of features and utility functions to the conditions of each scenario. To reduce the impact of inaccurate data, a correction component has been introduced that compensates for deviations in feature values from expected ones, minimizing forecast errors and increasing the stability of results.

Building a model for predicting the rationality of financial decisions in the context of digitalization of financial markets is becoming increasingly important. The active implementation of digital technologies, such as artificial intelligence, machine learning, and big data analysis, is changing the paradigm of the functioning of financial markets, contributing to their integration, increasing the speed of information flows, and increasing the availability of financial tools for a wide range of investors. This, in turn, complicates the analysis of market risks and increases the likelihood of making irrational decisions that can lead to significant capital losses. The applied value of the model for predicting financial decisions relates to its ability to optimize the process of assessing risks and investment returns, taking into account the multifactorial nature of the modern market environment. The use of predictive models makes it possible to identify possible negative trends in advance, analyze the impact of changes in legislation, financial regulation, or macroeconomic conditions on market stability. This is especially relevant in the context of constant changes that accompany the development of digitalization, where the importance of speed and validity of decisions becomes crucial factors for achieving competitive advantages. Modeling also makes it possible to increase the transparency and accuracy of the financial decision-making process by designing interactive tools that adapt to new data in real time. Thus, it provides managers and analysts with the necessary tools for systematic analysis of market conditions and justified forecasting, which, in turn, makes it possible to effectively manage financial flows, reduce risks, and promote sustainable development of the organization. The multi-vector predictive model of the rationality of financial decisions in the context of digitalization of financial markets integrates various methods of assessment and forecasting to ensure adaptability, flexibility, and accuracy. It combines key features that characterize the rationality of decisions, as well as approaches that take into account the specificity of digital markets.

5. Results of research on the multi-vector predictive model of financial decisions rationality in the context of digitalization

5. 1. Main components of the multi-vector predictive model of financial decisions rationality

The main components of the model are given below:

1. Determination of the main features and external factors:

– features of rationality of financial decisions (transparency, efficiency, risk management effectiveness, personalization, innovation and adaptability, reduction of transaction costs, integration of digital and financial tools);

– introduction of sets ($Z=\{Z_1, Z_2, ..., Z_n\}$ (rationality features) and $F=\{F_1, F_2, ..., F_m\}$ (external factors). External factors take into account the economic situation, market volatility, technological trends, etc.).

2. Adaptive determination of weight coefficients. Weight coefficients for features w_i and factors v_j are determined dynamically through the adaptive algorithm Adam (Adaptive Moment Estimation):

2. 1. Initialization of weights and parameters. Initial weights w_i for features and v_j for external factors are initialized with random values, the following parameters are also set: α – learning rate (usually a small value, for example, 0.001); β_1 and β_2 – exponential smoothing coefficients for the first and second moments (typical values $\beta_1=0.9$, $\beta_2=0.999$); ϵ is a small value to prevent division by zero (typically, $\epsilon=10^{-8}$).

2. 2. Calculation of gradients. At each iteration, the gradient of the loss function L is calculated by the weights for the features w_i and the factors v_j:

$$g_{w_i}=\frac{\partial L}{\partial w_i};\quad g_{w_j}=\frac{\partial L}{\partial v_i}. \tag{1}$$

2. 3. Updating the first and second moments of the gradients. Adam uses exponential smoothing for the first moment (the average of the gradients) and the second moment (the root mean square of the gradients).

2. 3. 1. The first moment for weight w_i and factor v_j:

$$m_{w_i}=\beta_1\cdot m_{w_i}^{(t-1)}+\left(1-\beta_1\right)\cdot g_{w_i};$$

$$m_{v_j}=\beta_1\cdot m_{v_j}^{(t-1)}+\left(1-\beta_1\right)\cdot g_{v_j}. \tag{2}$$

2. 3. 2. The second moment for weight w_i and factor v_j:

$$s_{w_i}=\beta_2\cdot s_{w_i}^{(t-1)}+\left(1-\beta_2\right)\cdot\left(g_{w_i}\right)^2;$$

$$s_{v_j}=\beta_2\cdot s_{v_j}^{(t-1)}+\left(1-\beta_2\right)\cdot\left(g_{v_j}\right)^2. \tag{3}$$

2. 3. 3. Offset correction. To avoid initial offset, the moments are corrected as follows:

$$\hat{m}_{w_i}=\frac{m_{w_i}}{1-\beta_1^t},\quad \hat{s}_{w_i}=\frac{s_{w_i}}{1-\beta_2^t},\quad \hat{m}_{v_i}=\frac{m_{v_i}}{1-\beta_1^t},\quad \hat{s}_{v_j}=\frac{s_{v_j}}{1-\beta_2^t}. \tag{4}$$

2. 3. 4. Updating the weights. The weights are updated according to the following formulas:

$$w_i^{(t+1)}=w_i^{(t)}-\alpha\cdot\frac{\hat{m}_{w_i}}{\sqrt{\hat{s}_{w_i}+\varepsilon}};\quad v_j^{(t+1)}=v_j^{(t)}-\alpha\cdot\frac{\hat{m}_{v_j}}{\sqrt{\hat{s}_{v_j}+\varepsilon}}. \tag{5}$$

The use of the utility function $U_i(Z_i)$ with the adjustment parameter β_i allows adaptive normalization of the values of features Z_i, taking into account the variability of market conditions. Let us consider this function in more detail and explain how it provides the flexibility of the model.

3. Nonlinear utility function for each feature. The use of the utility function $U_i(Z_i)$ with the adjustment parameter β_i adapts the normalization to market conditions. The utility function for feature Z_i looks like this:

$$U_i\left(Z_i\right)=\frac{z_i-z_{i,\min}}{z_{i,\max}-z_{i,\min}+\beta_i}, \tag{6}$$

where Z_i is the current value of the feature; $Z_{i,\min}$ and $Z_{i,\max}$ are the minimum and maximum values of the feature for a certain period or historical interval); β_i is a correction parameter that adapts the normalization to market conditions.

The normalization of values occurs in the range [0; 1]: the $Z_{i,\max}$–$Z_{i,\min}$ value defines the interval of possible values of feature Z_i for a certain period; by subtracting $Z_{i,\min}$ from the current value of Z_i, we shift the value so that the minimum value of the feature corresponds to zero. Dividing by $Z_{i,\max}$–$Z_{i,\min}$ normalizes the feature value to the range [0; 1], where 0 corresponds to the minimum value, and 1 to the maximum.

The correction parameter β_i is introduced into the denominator to adapt the normalization to current market conditions. If the market is characterized by instability or significant fluctuations, β_i can be adjusted to reduce the impact of these changes on the normalized feature value. For example, in a stable market, β_i may be close to zero, which means that the utility function will clearly reflect the relative changes between $Z_{i,\min}$ and $Z_{i,\max}$. In the case of an unstable market, increasing β_i reduces the sensitivity of the normalization to peak values, smoothing out sharp fluctuations and thus providing a more stable $U_i(Z_i)$ value.

If the values of the features change greatly, then β_i provides the possibility of adjustment to avoid a strong shift of $U_i(Z_i)$ to extreme values (0 or 1). For example, if the market is experiencing high fluctuations, β_i can reduce the Z_i–$Z_{i,\min}$:$Z_{i,\max}$–$Z_{i,\min}$ ratio, smoothing the values and providing more stable forecasts. This makes it possible to maintain the relative importance of each feature regardless of current conditions, which increases the flexibility of the model and its ability to reflect the importance of each feature taking into account market dynamics. The advantages of the utility function with an adjustment parameter are preservation of the relative importance of features; improved adaptability; versatility in use. Thus, the utility function $U_i(Z_i)$ with the adjustment parameter β_i adaptively changes the normalization, taking into account market conditions, and makes it possible to keep the values of the features in a range suitable for further analysis and forecasting.

4. Integral rationality index with a nonlinear combination of features. The integral rationality index R is calculated through a nonlinear combination of features, using the power exponent a_i, which makes it possible to take into account the interdependence of features and their nonlinearity:

$$R = \sum_{i=1}^{n} w_i \cdot U_i\left(Z_i\right)^{\alpha_i} + \sum_{j=1}^{m} v_j \cdot F_j, \tag{7}$$

where Z_i are the features that characterize the internal aspects of the rationality of financial decisions (for example, transparency, efficiency, adaptability); F_j are external conditions that affect the decision-making process (for example, economic conditions, market volatility); w_i is the individual weight of each feature, which determines its significance in the overall assessment. For example, in a volatile market, weights can be given to risk management, and under stable conditions they can be reduced; v_j is the weight for each external factor, which takes into account their impact on the decision. If an external factor (for example, an economic downturn) is significant, its weight can be increased); $U_i(Z_i)$ is the utility function. Each feature value is normalized and taken into account through the utility function $U_i(Z_i)$, which, as noted, reflects the importance of the feature depending on its current value and adapts to market conditions; a_i is a parameter that determines the nonlinearity of the impact of each feature. Depending on the value of a_i, the impact of the feature can be strengthened or weakened. For example, if $a_i>1$, the importance of high values of the attribute increases (enhancement effect), and if $a_i<1$, the model smooths out the influence of large values of the attribute (weakening effect). This makes it possible to take into account the effect of interdependence of attributes. For example, high adaptability and transparency in combination can reinforce each other under conditions of market volatility, which is reflected through the corresponding ai. The formula makes it possible to flexibly take into account the influence of both individual attributes and external factors due to the following: individual importance; nonlinear interdependence; adaptability to market conditions.

Thus, the integral index R combines values that reflect not only the current state of features and external factors but also their nonlinear impact on the overall rationality of the decision, which is critical for financial decisions in the context of digitalization. This makes it possible to take into account each feature in the context of its importance under current market conditions and provide a more accurate reflection of the rationality of the decision.

5. Scenario modeling for different market conditions. The model implements scenario modeling by generating different options for weights, utility functions, and parameters for different scenarios. The Monte Carlo method helps generate and analyze probable scenarios of events. For each scenario S_k, different values of $w_{i,k}$, $a_{i,k}$ and $v_{j,k}$ are used, which makes it possible to adjust the model to specific market conditions.

6. Adjustment to reduce the impact of inaccurate data. The correction component λ is added to minimize the impact of data inconsistencies:

$$R_{corr} = R + \lambda \cdot \sum_{i=1}^{n} \left(Z_i - \hat{Z}_i\right)^2. \tag{8}$$

This helps compensate for deviations of features from expected values and reduces the impact of data uncertainty.

The final expression of the rationality model, taking into account adaptability and nonlinearity, for each scenario looks like this:

$$R_{corr} = \sum_{i=1}^{n} w_i \cdot \left(\frac{z_i - z_{i,\min}}{z_{i,\max} - z_{i,\min} + \beta_i}\right)^{\alpha_i} + \\ + \sum_{j=1}^{m} v_j \cdot F_j + \lambda \cdot \sum_{i=1}^{n} \left(z_i - \hat{z}_i\right)^2. \tag{9}$$

The multi-vector nature of the model makes it possible to take into account all aspects of the digital transformation of financial markets and minimize the impact of inaccuracies. The formula makes it possible to flexibly take into account the impact of both individual features and external factors due to the following: individual significance; nonlinear interdependence; adaptability to market conditions. Thus, the integral index R combines values that reflect not only the current state of features and external factors but also their nonlinear impact on the overall rationality of the decision, which is critical for financial decisions in the context of digitalization. This makes it possible to take into account each feature in the context of its importance under current market conditions and provide a more accurate reflection of the rationality of the decision.

The constructed model is multi-vector since it integrates several different vectors of influence that take into account both internal features of the rationality of financial decisions and external market factors. The basis of the model is a set of features that reflect key aspects of rationality, such as transparency, efficiency, adaptability, risk management effectiveness, and innovation. Each of these features is represented as a vector with individual weights that determine its significance in the overall assessment. These weights are adapted according to market conditions, which provides a dynamic reflection of the importance of each feature in the forecasting process. In addition, another vector of external factors is included in the model structure, which reflects the main market influences, such as economic conditions, market volatility and other macroeconomic conditions. The weight of each external factor is also adjusted using an adaptive algorithm, which allows the model to quickly respond to changes in the external environment and integrate them into the forecasting process.

The model uses a utility function for each feature with a correction parameter, which normalizes the values within [0; 1] and adapts them to specific market conditions. This once again emphasizes its multi-vector nature since the model makes it possible to individually adjust the values of individual features that affect the overall rationality index. It is also important to note that the model provides the possibility of scenario modeling, where for each market scenario, in particular using the Monte Carlo method, both weights and utility functions for features and factors are adjusted. This allows the model to take into account various combinations of influences, supporting the integration of several influence vectors under conditions of uncertainty.

Thus, the multi-vector nature of the model is implemented through a multi-dimensional representation of features and factors, which makes it possible to integrate the influence of each of them on predicting the rationality of financial decisions in the context of digitalization. Such a structure provides the flexibility, adaptability, and accuracy necessary for informed financial decisions in dynamic digital markets. The advantages of the model for predicting the rationality of financial decisions in the context of digitalization are important since financial markets are characterized by high dynamics and often unpredictable changes. Advantages of the multi-vector model:

1. Adaptability to dynamic changes. The adaptability of the model is ensured by its ability to respond to changes in market conditions and external factors. An important element of adaptability is the automatic adjustment of weight coefficients and adjustments, which is achieved through the use of algorithms such as Adam and the use of the utility function $U_i(Z_i)$, with the adjustment parameter β_i. This allows the model to adapt to any market fluctuations and instability. Thanks to the adaptive optimization algorithm Adam, the model automatically adjusts the weights for features and external factors in accordance with current conditions. This is important because under conditions of increasing market volatility, the model can reduce the weights of less significant indicators and increase them for those that play a key role in risk conditions. In turn, the use of adjustments helps reduce errors due to input data inconsistency, minimizing the likelihood of errors in forecasts arising from market changes. This allows the model to provide more stable results even with significant market fluctuations.

2. Flexibility in scenario modeling. The multi-vector model supports scenario modeling, which is key to analyzing possible market scenarios. Flexibility in scenario modeling allows the model to be used for forecasting under different conditions and scenarios, which significantly increases the accuracy and reliability of forecasts. The Monte Carlo method allows modeling to be carried out taking into account a large number of possible scenarios. The model generates random values for key variables, simulating different market conditions and assessing their impact on the effectiveness of financial decisions. The weights of features and factors can be individually configured for each scenario, allowing the model to adapt to the conditions of a specific scenario and provide accurate forecasts within the given conditions. This is especially important for financial decisions that depend on market conditions.

3. Risk reduction and risk management efficiency. The model contributes to risk reduction due to its approach to risk assessment and management. This is achieved through a comprehensive integration of risk management techniques such as Monte Carlo scenario modeling, Bayesian networks, and other forecasting tools. Using Bayesian networks, the model takes into account uncertainty and conditional probabilities, which allows it to identify relationships between events and potential risks. This helps assess likely consequences based on current data and historical trends. Scenario modeling and risk analysis enable the model to evaluate decision options, taking into account possible risks, and help to avoid erroneous decisions that can be triggered by market instability. In turn, using risk-based forecasting, the model helps avoid large losses by choosing optimal scenarios and decisions that take into account the worst possible consequences.

4. Personalization and optimization. Personalization is provided by using machine learning algorithms, which makes it possible to customize the model to specific needs and features of the user, in particular to individual requests of investors or companies. This increases the efficiency of decisions made and ensures resource optimization. Thus, adaptation to individual needs occurs based on the use of machine learning and makes it possible to take into account the individual parameters and needs of each client. For example, the model can take into account the specific requirements of the investor regarding risk, potential profit, or investment term. Optimization of financial decisions is provided by using optimization algorithms; the model is able to find the best combinations of solutions that maximize the utility for the client, taking into account his needs. This allows for more effective management of financial resources. The model can continue to learn from new data, which constantly increases its accuracy. This is especially important for a digitalized market, where information changes rapidly, and customer needs and market conditions are updated. A multi-vector model for predicting the rationality of financial decisions provides powerful tools for making informed decisions under complex and dynamic market conditions. Its adaptability, flexibility in scenario modeling, risk reduction, and personalization build a solid foundation for effective planning that takes into account internal and external factors.

5. 2. Adaptive tuning and testing of a multi-vector model of financial decisions rationality in the context of digitalization

Adaptive tuning and testing of a multi-vector model of financial decisions rationality was performed on the example of several financial companies operating in highly digitalized financial markets.

The proposed multi-vector model takes into account the impact of digitalization on forecasting the rationality of financial decisions through an adaptive architecture that reflects new capabilities of digital technologies for fast data processing, increasing the accuracy of forecasts and personalizing decisions. The digitalization of financial markets has caused significant changes in the volume and availability of information, making the process of making financial decisions faster and more convenient, and therefore, the requirements for forecasting models have increased significantly. In this regard, the model uses the adaptive optimization algorithm Adam, which provides dynamic adjustment of weight coefficients for each feature and external factor (Fig. 1).

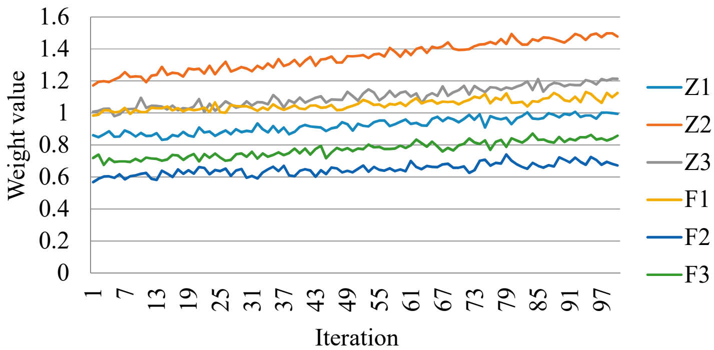

Fig. 1. Adam Adaptive weight adjustment using the Adam algorithm

In the model of forecasting the rationality of financial decisions, adaptive adjustment of weight coefficients using the Adam algorithm involves changing the weights of features and external factors in accordance with the market situation. At the initial stage of modeling, the weights are initialized with random values, after which the gradient of the loss function L is calculated for each of the weight coefficients. To reduce fluctuations in the process of updating the weights, exponential smoothing of gradients is used, which provides a gradual adjustment of the weight based on previous values. The process of updating the weights includes taking into account historical changes and responding to current market fluctuations. Weights are adapted taking into account changes in market conditions, such as the level of volatility, macroeconomic indicators, and technological trends, which directly affect financial decisions. Variations in utility functions for each feature are also taken into account, which provides adjustment of the influence of various factors depending on the market situation. An important aspect is the consideration of forecasting errors in previous iterations, which makes it possible to minimize errors and increase the accuracy of predictions in subsequent calculations.

Given this, the model is able to automatically change the weights in accordance with new market conditions, reducing forecasting errors under conditions of high market volatility. In addition to adaptability, the model also provides a utility function with a correction parameter β_i, which makes it possible to normalize the values of the features within [0; 1] taking into account market conditions (Fig. 2).

Fig. 2 illustrates the effect of adjustment parameter β on the normalization of utility function Ui (Zi) and demonstrates how the adaptation of the model depends on changes in market conditions. The X-axis shows the value of the Zi feature in the range from 0 to 1, and the Y-axis shows the value of the utility function Ui (Zi). Each of the curves corresponds to different values of the parameter β, which determines the level of smoothing of the normalization. For a small value of β, for example, 0.01, the function is almost linear, which means that the model is highly sensitive to changes in the Zi feature, which is effective for analyzing stable market conditions. When β is increased to 0.1–0.5, a noticeable smoothing occurs, which helps reduce the impact of random fluctuations. For β values of 1–2, the function becomes less sensitive to changes in the feature, which is useful under conditions of high market volatility, when it is necessary to avoid excessive response to short-term fluctuations. The larger the value of β, the smoother the Ui (Zi) function changes, which provides a more stable adaptation to an unstable market environment. Thus, the plot shows that the choice of the adjustment parameter β is an important tool for controlling the sensitivity of the model to changes in market conditions.

This makes it possible to smooth out sharp changes in input data, which often arise due to sudden fluctuations in digital markets, and, thus, maintain stability in the forecasting process. At the same time, taking into account the nonlinear interaction of features and external factors through the power indicator α_i allows the model to reflect complex dependences between various parameters. This is important for ensuring the rationality of decisions, especially when changes occur simultaneously in several market segments. Digitalization also expands the possibilities of analysis and forecasting through the use of large volumes of data in real time. Therefore, the multi-vector model provides for the possibility of scenario modeling, in particular using the Monte Carlo method, which makes it possible to generate and take into account various options for the development of the market situation. This provides a more accurate analysis under high uncertainty, which is characteristic of digital markets, where changes can be unpredictable. It is also important that the model provides an individual approach to each client or investor, which is implemented through personalization of decisions. Thanks to machine learning algorithms, the model is able to take into account the individual needs and risk profiles of users, adapting to their financial goals and situations, which increases the accuracy and rationality of decisions. Thus, the impact of digitalization on predicting the rationality of financial decisions in the proposed model is taken into account through adaptability, flexibility of scenario modeling, stability in the event of data fluctuations, and the possibility of personalization. This provides an accurate reflection of market dynamics, increasing the reliability and rationality of financial decisions in digital markets.

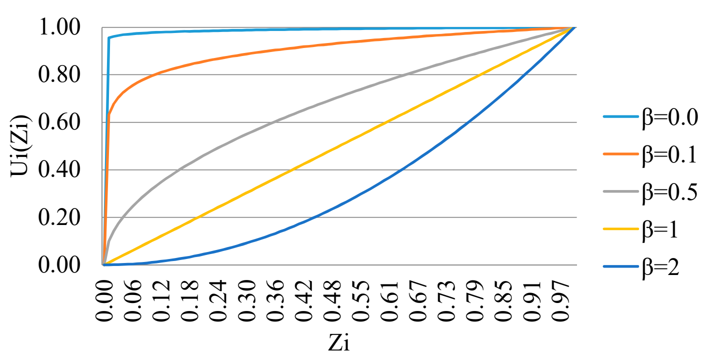

Fig. 2. Effect of the correction parameter β on the normalization of the utility function Ui (Zi)

Next, the proposed multi-vector model is considered using the example of several Ukrainian financial companies (Moneyveo, LeoGaming Pay, Ukrfinzhitlo, FC “European Microfinance Alliance”, FC “Smart Pay”) over the period 2018–2023. These companies are united by the fact that they operate in highly digitized financial markets and regularly make investment decisions, decisions on financing, assessment of financial stability, and risk management.

The initial data for performing the necessary calculations are given in Table 1; the results of step-by-step calculations – in Tables 2, 3.

A plot was constructed based on the results of our calculations (Fig. 3).

Our results in the plot demonstrate the dynamics of the adjusted rationality index R_{corr} for each of the analyzed companies in the period 2018–2023. They reflect how different financial decisions and strategic approaches respond to changes in external market conditions and internal characteristics of the companies. Changes in R_{corr} values over years indicate the ability of companies to adapt their decisions to market conditions, such as increased volatility, changing economic conditions, or the introduction of new digital technologies. For example, sharp fluctuations in the index for individual companies may indicate a significant impact of external factors, which forced the companies to make rapid changes in capital management, operating costs, or risks.

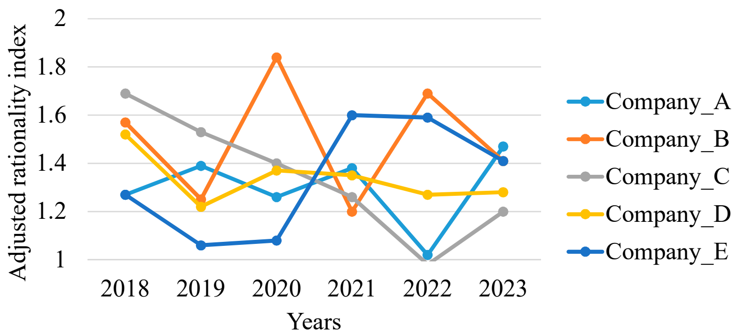

Fig. 3. Adjusted rationality index R_{corr} for each company over the period 2018–2023

Note: constructed by authors based on data from respective companies.
Symbols: Company_A – Moneyveo;
Company_B – LeoGaming Pay;
Company_C – Ukrfinzhytlo;
Company_D – European Microfinance Alliance;
Company_E – Smart Pay

Table 1

Input data for model calculation

Financial companies	Year	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	F_1	F_2	F_3
Moneyveo	2018	1.0488	0.7646	0.6590	0.8186	1.2253	0.6494	0.6647	1.1961	1.1455	1.1910
Moneyveo	2019	1.2152	1.2742	0.6104	1.1674	1.0013	1.3681	1.1215	0.8868	0.8470	1.1506
Moneyveo	2020	1.1028	0.9562	1.1563	0.6318	1.4561	0.6625	1.0772	1.0652	1.0070	0.9353
Moneyveo	2021	1.0449	1.0684	0.6382	1.2163	1.1440	1.1156	0.7379	0.9053	0.8528	1.1846
Moneyveo	2022	0.9237	0.5188	0.6966	0.7894	0.9239	0.6238	1.4342	0.8083	1.0867	0.8927
Moneyveo	2023	1.1459	1.1176	0.8687	0.6832	1.1064	1.3480	1.1140	1.1034	0.9584	1.1797
LeoGaming Pay	2018	0.9376	1.1121	1.3210	1.0865	0.5192	1.3073	1.0356	0.9280	1.0262	1.1766
LeoGaming Pay	2019	1.3918	1.1169	0.5971	0.5201	0.8016	1.0691	1.0899	0.9534	0.8733	1.1197
LeoGaming Pay	2020	1.4637	1.4437	1.3379	1.3289	1.1602	0.9072	1.2301	1.0353	0.8579	1.0522
LeoGaming Pay	2021	0.8834	1.1818	0.5961	0.5047	0.7901	0.5692	0.8119	1.1324	0.9952	1.1497
LeoGaming Pay	2022	1.2917	0.8595	1.4765	1.1778	1.1180	1.1974	0.8982	1.0516	0.9422	0.9172
LeoGaming Pay	2023	1.0289	0.9370	0.9687	0.7700	0.9288	0.9535	0.7098	1.1491	1.1762	1.1396
Ukrfinzhitlo	2018	1.0680	1.1976	1.4768	1.2352	0.6355	1.2221	0.6862	0.9094	1.1061	1.0472
Ukrfinzhitlo	2019	1.4256	0.5602	1.1048	1.4622	0.7983	1.3664	1.4444	1.1192	1.0995	0.8053
Ukrfinzhitlo	2020	0.5710	1.1668	1.2393	0.7488	1.0700	1.4755	1.2396	0.8743	1.1615	0.9389
Ukrfinzhitlo	2021	0.5871	1.1706	0.5392	1.0762	1.0909	1.3558	0.9905	1.1811	0.8334	0.8593
Ukrfinzhitlo	2022	0.5202	0.7104	0.7828	1.0920	1.0743	0.5117	0.7274	1.0750	1.0209	1.1927
Ukrfinzhitlo	2023	1.3326	0.6289	0.6202	1.0723	1.1532	0.8600	0.7544	0.8862	1.0338	0.9913
European Microfinance Alliance	2018	1.2782	0.8154	0.7961	0.7231	1.1521	1.2300	0.5580	1.1789	1.1848	0.9990
European Microfinance Alliance	2019	1.3700	0.8637	0.6187	1.4527	0.9314	0.6716	0.9344	1.0923	0.9169	1.0558
European Microfinance Alliance	2020	1.4786	1.0702	0.8180	0.9471	1.3965	1.0210	0.8118	0.9016	0.8963	0.9474
European Microfinance Alliance	2021	1.2992	0.9386	0.9143	1.3464	0.8676	0.5543	1.1963	0.8853	0.8401	0.8548
European Microfinance Alliance	2022	0.9615	1.4884	0.5641	1.1995	0.9359	0.7000	0.8778	1.0073	0.8066	1.1288
European Microfinance Alliance	2023	1.2805	0.6020	1.1925	0.7974	1.3919	0.5185	0.6796	0.8103	1.1718	0.8759
Smart Pay	2018	0.6183	0.7089	1.0666	1.3138	1.3062	1.2937	0.5247	0.8830	1.0680	1.0045
Smart Pay	2019	1.1399	0.6613	0.7654	0.8965	1.2039	0.7239	0.5672	0.9699	1.1141	0.8897
Smart Pay	2020	0.6434	1.1531	1.0232	1.3811	0.6002	0.8454	1.1794	0.9497	0.9127	0.8391
Smart Pay	2021	1.4447	0.7533	0.5939	1.0813	1.4195	1.4281	0.9537	0.9854	1.0346	1.1449
Smart Pay	2022	1.0218	0.9663	1.0759	1.3817	1.2142	1.2044	1.0366	0.9111	0.8256	1.1892
Smart Pay	2023	0.9147	0.7444	1.4293	1.1925	1.4988	0.5318	1.3967	1.0347	0.9943	1.1843

Note: constructed by authors based on data from respective companies.

Table 2

Results of $U_i(Z_i)$ calculation

Financial companies	Year	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	F_1	F_2	F_3
Moneyveo	2018	0.4941	0.0732	0.0000	0.1282	0.7731	0.0000	0.2086	1.1961	1.1455	1.1910
Moneyveo	2019	0.1514	0.7241	0.0176	0.5905	0.3817	0.8625	0.5342	0.8868	0.8470	1.1506
Moneyveo	2020	0.4752	0.0000	0.4421	0.0000	0.8714	0.0000	0.4514	1.0652	1.0070	0.9353
Moneyveo	2021	0.4282	0.4498	0.1595	0.7146	0.4683	0.5699	0.0000	0.9053	0.8528	1.1846
Moneyveo	2022	0.4104	0.0000	0.1144	0.0000	0.0000	0.1395	0.8151	0.8083	1.0867	0.8927
Moneyveo	2023	0.3674	0.6546	0.2357	0.0000	0.2551	0.8819	0.4951	1.1034	0.9584	1.1797
Leogaming Pay	2018	0.3665	0.5299	0.6227	0.4880	0.0000	0.8555	0.7612	0.9280	1.0262	1.1766
Leogaming Pay	2019	0.5066	0.5645	0.0000	0.0000	0.0062	0.4922	0.5038	0.9534	0.8733	1.1197
Leogaming Pay	2020	0.7977	0.6418	0.6794	0.7717	0.5701	0.2648	0.7113	1.0353	0.8579	1.0522
Leogaming Pay	2021	0.2772	0.6116	0.0917	0.0000	0.0000	0.0151	0.1197	1.1324	0.9952	1.1497
Leogaming Pay	2022	0.7849	0.2744	0.7880	0.5204	0.4660	0.8531	0.1970	1.0516	0.9422	0.9172
Leogaming Pay	2023	0.1815	0.4253	0.3304	0.1309	0.0000	0.4625	0.0345	1.1491	1.1762	1.1396
Ukrfinzhytlo	2018	0.5162	0.6424	0.7692	0.6876	0.1273	0.7447	0.2406	0.9094	1.1061	1.0472
Ukrfinzhytlo	2019	0.5746	0.0000	0.6742	0.8594	0.0000	0.8603	0.8455	1.1192	1.0995	0.8053
Ukrfinzhytlo	2020	0.0000	0.2772	0.5504	0.1295	0.4783	0.8798	0.7274	0.8743	1.1615	0.9389
Ukrfinzhytlo	2021	0.0000	0.5957	0.0000	0.5739	0.3980	0.8138	0.4082	1.1811	0.8334	0.8593
Ukrfinzhytlo	2022	0.0000	0.1543	0.1889	0.4055	0.3611	0.0000	0.0000	1.0750	1.0209	1.1927
Ukrfinzhytlo	2023	0.6640	0.0341	0.0000	0.5865	0.3223	0.3630	0.0852	0.8862	1.0338	0.9913
European Microfinance Alliance	2018	0.7573	0.1400	0.1290	0.0000	0.6930	0.7550	0.0497	1.1789	1.1848	0.9990
European Microfinance Alliance	2019	0.4628	0.3078	0.0287	0.8508	0.2503	0.0000	0.3539	1.0923	0.9169	1.0558
European Microfinance Alliance	2020	0.8110	0.1501	0.0000	0.3491	0.8108	0.3880	0.0000	0.9016	0.8963	0.9474
European Microfinance Alliance	2021	0.6661	0.2645	0.6045	0.8453	0.1025	0.0000	0.7409	0.8853	0.8401	0.8548
European Microfinance Alliance	2022	0.4489	0.7809	0.0000	0.5494	0.0288	0.2342	0.1734	1.0073	0.8066	1.1288
European Microfinance Alliance	2023	0.5813	0.0000	0.5427	0.1722	0.6651	0.0000	0.0000	0.8103	1.1718	0.8759
Smart Pay	2018	0.0000	0.0000	0.3834	0.7931	0.8617	0.8378	0.0000	0.8830	1.0680	1.0045
Smart Pay	2019	0.0000	0.1025	0.2234	0.3434	0.7626	0.0648	0.0000	0.9699	1.1141	0.8897
Smart Pay	2020	0.0646	0.2593	0.2682	0.8295	0.0000	0.1979	0.6251	0.9497	0.9127	0.8391
Smart Pay	2021	0.8022	0.0000	0.0882	0.5790	0.8329	0.8872	0.3488	0.9854	1.0346	1.1449
Smart Pay	2022	0.5103	0.3604	0.4421	0.7936	0.6969	0.8618	0.3565	0.9111	0.8256	1.1892
Smart Pay	2023	0.0000	0.1808	0.7673	0.7678	0.8186	0.0142	0.8173	1.0347	0.9943	1.1843

Note: constructed by authors based on data from respective companies.

Table 3

Results of calculating R

Financial companies	Year	R
1	2	3
Moneyveo	2018	1.2289
Moneyveo	2019	1.3656
Moneyveo	2020	1.2389
Moneyveo	2021	1.3375
Moneyveo	2022	0.9848
Moneyveo	2023	1.4493
Leogaming Pay	2018	1.5408
Leogaming Pay	2019	1.2240
Leogaming Pay	2020	1.7989
Leogaming Pay	2021	1.0822
Leogaming Pay	2022	1.6631
Leogaming Pay	2023	1.2034
Ukrfinzhytlo	2018	1.6539
Ukrfinzhytlo	2019	1.4827
Ukrfinzhytlo	2020	1.3635
Ukrfinzhytlo	2021	1.2270
Ukrfinzhytlo	2022	0.9450
Ukrfinzhytlo	2023	1.1859

Continuation of Table 3

1	2	3
European Microfinance Alliance	2018	1.5039
European Microfinance Alliance	2019	1.1903
European Microfinance Alliance	2020	1.3529
European Microfinance Alliance	2021	1.3563
European Microfinance Alliance	2022	1.2434
European Microfinance Alliance	2023	1.2415
Smart Pay	2018	1.2320
Smart Pay	2019	1.0380
Smart Pay	2020	1.0433
Smart Pay	2021	1.5649
Smart Pay	2022	1.5784
Smart Pay	2023	1.3673

Note: constructed by authors based on data from respective companies.

6. Discussion of results based on building a multi-vector predictive model of the rationality of financial decisions

The modeling results are explained by the effectiveness of using the adaptive Adam algorithm, the utility function with a correction parameter, and scenario modeling using the Monte Carlo method. This makes it possible to take into account the complex interaction of internal features (efficiency, transparency, adaptability) and external factors (economic conditions, market volatility). Tables 2–4 and Fig. 1–3 reflect the dynamics of changes in the rationality index R for the analyzed companies and demonstrate the model's ability to adapt to changes in market conditions.

Regarding the features of the proposed method and the results obtained compared to existing ones, the proposed model integrates an adaptive approach to determining weight coefficients and takes into account nonlinear interdependences between features and factors. Compared with conventional forecasting methods, the model provides flexibility and accuracy due to scenario modeling and the ability to adjust data. For example, Table 3 shows how the utility function $U_i(Z_i)$ normalizes the feature values for different companies. This goes beyond the limitations of static models such as those proposed in [1–6], which focus on simple regression methods or time series analysis.

As a result of the study, the main features and external factors that affect the forecasting results have been identified; weight coefficients were established for the model components; a nonlinear utility function was constructed for each feature. In addition, an integral rationality indicator with a nonlinear combination of features was proposed; adaptive tuning and testing of a multi-vector model of the rationality of financial decisions under the conditions of digitalization were carried out.

Our study builds on existing scientific knowledge [13–16, 26–32] by devising a multi-vector predictive model of the rationality of financial decisions. The model is based on:

1) a critical analysis of the tools for predicting the rationality of decisions under the conditions of digitalization of financial markets;

2) proving that each of them has unique strengths and limitations.

This requires the use of an integrated approach to forecasting. The model combines adaptive optimization algorithms for setting weight coefficients; a utility function with a correction parameter that normalizes the values of the features according to market conditions. In addition, scenario modeling was used to generate and analyze probable market scenarios; as well as Bayesian networks to assess uncertainties and conditional probabilities of events. This allowed our multi-vector model to:

1) respond adaptively to dynamic changes in market conditions; achieve stability under conditions of market instability even in cases of high volatility;

2) adjust the normalization of features in accordance with current market conditions, ensuring the stability of results during significant fluctuations;

3) simulate the level of rationality of decisions under different scenarios of market dynamics;

4) increase the reliability of decisions through advanced risk management.

It has been proven that thanks to the integrated approach, the multi-vector model contributes to achieving high forecast accuracy, stability, and reliability in making financial decisions under conditions of instability of financial markets.

The practical value of these results is that they can serve as an important tool for strategic planning and assessing investment attractiveness. Such data allows company managers to assess the effectiveness of their decisions in retrospect and adapt the current strategy in accordance with the growing market requirements and internal indicators of sustainability. For investors, these indices can serve as a guide in determining which companies have stable and rational approaches to managing their finances, as well as how they react to market disturbances. A high level of R_{corr} indicates the rationality of the decisions made, which can be a signal for long-term investment.

The analytical conclusions from this study can be addressed to various stakeholders. For top managers of companies, these data make it possible to clarify the effectiveness of management decisions and flexibility under difficult market conditions, which could contribute to increasing corporate stability and market position. For investors and financial analysts, these indices provide an additional level of information transparency and help make informed investment decisions, focusing on the rationality and stability of the company. At the same time, for regulators and financial authorities, such a model can serve as an indicator of the health of the financial market, as it helps identify companies with a high level of risks or, conversely, with increased adaptability to market changes.

Thus, the results of the model have high practical value, allowing for both internal and external analysis of companies in a digitalized financial environment. This model supports the validity of financial decisions, optimizes risk management, and contributes to increasing the profitability and stability of companies in dynamic markets.

In summary, the main characteristics of the proposed model are as follows:

1. Model components: features, weights, integral rationality index. The main features of the rationality of financial decisions include transparency, efficiency, risk management effectiveness, personalization, innovation, adaptability, reduced transaction costs, integration of digital and financial tools. Weights are determined adaptively through algorithms such as Adam, providing dynamic adjustment depending on market conditions. The integral rationality index is calculated through a nonlinear combination of features and external factors.

2. Vectors confirming the multi-vector nature: a vector of features reflecting the internal aspects of the rationality of decisions (for example, transparency, adaptability); a vector of external factors, such as economic conditions and market volatility, that influence the decision-making process. Both vectors are integrated thanks to an adaptive algorithm that automatically adjusts the weights in response to changes in the external environment.

3. List of integrated forecasting tools:

a) adaptive optimization algorithms, such as Adam, for adjusting weighting factors;

b) a utility function with an adjustment parameter that normalizes the values of features according to market conditions;

c) scenario modeling using the Monte Carlo method to generate and analyze probable market situation scenarios;

d) Bayesian networks for assessing uncertainties and conditional probabilities of events, which makes it possible to identify risks and the relationships between them.

This model provides flexibility, adaptability, and accuracy to justify financial decisions under the conditions of digital transformation of markets.

The model provides the ability to adaptively adjust parameters depending on changes in market conditions, which increases its accuracy and stability in forecasting. Thanks to scenario modeling using the Monte Carlo method and a utility function with an adjustment parameter, the model makes it possible to reduce risks and adapt to different market scenarios. This creates a reliable basis for making effective financial decisions under the conditions of digital transformation of markets.

Further research should be directed towards improving adaptive forecasting methods, integrating scenario modeling with big data, and developing tools to assess the rationality of financial decisions in the context of digital market transformation.

This study has the following limitations:

1. Application limits: the model is effective only for highly digitized financial markets.

2. Reproducibility: the results depend on the correctness of the input data and the choice of parameters.

3. Data ranges: the model is sensitive to high volatility of market conditions, which may reduce the accuracy of forecasts.

4. Application conditions: the need for high computing power due to the use of the Monte Carlo method.

Suggestions for eliminating the shortcomings of this study in the future:

1. Limited sample size: the analysis was conducted on a small number of companies operating in digital markets. In the future, it is worth expanding the sample to include companies from other industries.

2. High computational complexity: the proposed algorithms require significant resources, so optimization of computational processes may become one of the areas of development.

3. Insufficient analysis of external factors: it is worth adding more macroeconomic variables to increase the accuracy of forecasts.

Further development of the research may be aimed at integrating the latest machine learning technologies to increase the accuracy of forecasts; analyzing the impact of global financial events on the effectiveness of the model; expanding the functionality for different markets.

The main possible difficulties: the complexity of developing universal algorithms that take into account all possible factors; the need for large amounts of data for training models; ensuring the interpretation of results for a wide range of users.

7. Conclusions

1. The rationality of financial decisions is determined by such features as transparency, efficiency, risk management effectiveness, personalization, innovation, adaptability, cost reduction, and integration of digital tools. These features are systematized into a set Z (non-linear utility function), which interacts with a set of external factors F, which includes the economic situation, market volatility, and technological trends. A comprehensive analysis of these sets allows for effective, adaptive, and justified financial decisions taking into account the changing environment. The integral rationality indicator R provides a combination of features and external factors through their weight coefficients and nonlinear impact, taking into account interdependence and adaptability to market conditions. Using the power α_i allows for strengthening or smoothing the impact of each feature depending on its value and importance in the current context. This approach, unlike existing ones, provides an accurate assessment of the rationality of financial decisions in a dynamic environment, allowing for adaptive response to external and internal changes.

2. Adaptive determination of weight coefficients in financial decision models ensures their compliance with dynamic market conditions using algorithms such as gradient descent and Adam. The Adam algorithm, due to its adaptive learning speed, efficiency in working with nonlinear data, and ability to work stably under conditions of volatility, is optimal for building accurate and fast forecasts. Its application makes it possible to constantly adjust the weights of parameters, taking into account current market dynamics, reducing the model error, and increasing its efficiency. The utility function $U_i(Z_i)$ with the correction parameter β_i provides adaptive normalization of features in the range [0; 1], taking into account market conditions. The correction parameter β_i smoothes the impact of fluctuations in unstable markets, avoiding a shift of values to extreme points, which increases the accuracy of forecasts. This approach differs from existing ones in that it allows for the preservation of the relative importance of features, adaptability to market scenarios, and versatility in working with different types of data. Scenario modeling makes it possible to adapt the model to different market conditions by generating options for weights, utility functions, and parameters for each scenario. The use of the Monte Carlo method provides an analysis of probable scenarios of events, creating different configurations of the parameters $w_{i,k}$, $\alpha_{i,k}$, and $\nu_{j,k}$. This approach

differs from existing ones in that it increases the flexibility of the model and its ability to take into account specific market conditions for more accurate forecasting.

The correction component λ in the model minimizes the impact of inaccurate data, compensating for deviations of features from expected values. The formula takes into account the individual significance of features, their nonlinear interdependence and adaptability to market conditions, which ensures stability and accuracy of estimates. The multi-vector structure of the model, unlike mono- and bivector models, makes it possible to effectively reflect the rationality of financial decisions even under conditions of digital transformation and uncertainty.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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