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Том 4, № 1, 2026

SMART ECONOMY, ENTREPRENEURSHIP AND SECURITY

Vol. 4, № 1, 2026

НАУКОВИЙ ЖУРНАЛ

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ARTIFICIAL INTELLIGENCE IN AUTOMATED FINANCIAL RISK MANAGEMENT SYSTEMS

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Abstract. *The article is aimed at studying the use of artificial intelligence in automated financial risk management systems to improve the accuracy, efficiency and efficiency of managerial decision-making in the financial sector. The study consists in a comprehensive study of the theoretical and methodological foundations of the use of artificial intelligence in management systems, analysis of modern approaches to the classification and assessment of financial risks using machine learning algorithms, formation of the architecture of the decision support system based on forecasting models, as well as assessment of the effectiveness of the built models based on the results of simulation modeling. Within the framework of the study, a model for forecasting the credit risk of bank customers has been developed, which allows assessing solvency based on historical data and modern machine learning methods. The research method is modeling using machine learning tools, including neural networks and ensemble learning methods (Random Forest), as well as data analysis using platforms to visualize results and evaluate the effectiveness of models. Particular attention is paid to data preparation, selection of relevant features, evaluation of model accuracy, and construction of interpreted visualizations such as SHAP graphs, ROC curves, etc. The result of the study was the creation of an effective model for predicting credit risk, which demonstrates a sufficiently high level of classification accuracy and the ability to adapt to changes in incoming conditions. The practical significance of the study lies in the possibility of implementing the developed model into the existing automated financial risk management systems of banking institutions, which will reduce the level of credit losses, increase financial stability and provide more accurate risk management. This approach contributes to the development of intelligent financial systems, increasing the level of automation of managerial decisions and strengthening the competitiveness of financial institutions in modern market conditions.*

Keywords*: artificial intelligence, financial risks, machine learning, credit risk, neural networks, automated control system, forecasting, classification.*

1. Introduction

Financial risks are an integral part of the operations of any business or financial institution, and their effective management is key to ensuring stability and profitability. The main classifications of financial risks include: market risks associated with fluctuations in asset prices, interest rates, or exchange rates; credit risks arising in the event of insolvency of counterparties; operational risks due to internal failures, errors or fraud; liquidity risks associated with the inability to quickly sell assets without significant losses; as well as legal and reputational risks arising from non-compliance with regulatory requirements or negative assessment of activities by partners and clients.

Sources of financial risks are divided into external and internal. External ones include economic instability, political changes, natural disasters, and market fluctuations that affect the financial performance of the enterprise. Internal sources are associated with imperfection of management processes, insufficient control, human errors and technological failures. A systematic approach to risk classification allows you to more effectively identify potential threats and develop adaptive strategies for their neutralization.

Thus, financial risks are a complex phenomenon that encompasses various types and sources of uncertainty, and their management requires the use of integrated approaches, including the use of modern automated systems and artificial intelligence technologies to improve the quality of analysis and forecasting of risk factors. Financial risk management is a key area in the activities of financial institutions, banks and corporations. The main goal of financial risk management is to timely identify, assess and minimize possible threats, which allows you to make informed decisions on capital preservation and maintaining financial stability.

In modern conditions of dynamic market development and high competition, automated financial risk management systems have become an integral part of collecting, processing and analyzing large amounts of data for timely detection of potential threats and decision-making. These systems integrate a variety of tools and technologies, including statistical analysis and modeling techniques, as well as the latest intelligent approaches. In recent years, much attention has been paid to the use of artificial intelligence algorithms, which can improve the accuracy of predictions and the adaptability of systems to changing conditions. Structurally automated financial risk management systems consist of data collection modules, analytical tools, decision support systems, as well as monitoring and control modules [1].

The current economic situation is characterized by a high degree of uncertainty, complexity of financial processes and increased risks faced by enterprises, banks and other financial institutions. Under such conditions, effective financial risk management becomes a key task that requires the introduction of the latest approaches and tools. One of the most promising areas is the use of artificial intelligence (AI) technologies, which allow automating data analysis, identifying hidden patterns, and making informed management decisions in conditions of uncertainty [5].

Artificial intelligence is becoming one of the key tools for transforming the financial sector, providing automation of complex processes, increasing the accuracy of forecasts, and improving risk management. With the ability to process large amounts of data and find hidden patterns, AI technologies allow financial institutions to respond effectively to rapid market changes and minimize possible losses.

The article is aimed at studying the use of artificial intelligence in automated financial risk management systems to improve the accuracy, efficiency and efficiency of managerial decision-making in the financial sector.

The objectives of the study are:

1) description and analysis of modern methods and approaches to financial risk management in banks and insurance companies and assessment of financial risks using machine learning algorithms;
2) comprehensive study of the theoretical and methodological foundations of the use of artificial intelligence in financial risk management systems;
3) study of the opportunities, advantages and problems of using artificial intelligence in automated financial risk management systems;
4) analysis of the features of deep learning models, decision trees, ensemble methods, as well as criteria for evaluating their effectiveness
5) formation of the architecture of the decision support system based on forecasting models;
6) exploring the possibility of using artificial intelligence to improve the accuracy of financial risk forecasting, fraud detection, and credit and insurance risk management;
7) assessment of the main challenges and limitations in the use of AI for financial risk management;
8) evaluation of the effectiveness of the built models based on the results of simulation modeling;
9) development of a model for forecasting the credit risk of the bank's customers, which allows assessing solvency on the basis of archival data and modern methods of machine learning, which recognizes the novelty of the research.

Thus, the study consists in generalizing theoretical and methodological approaches to the use of artificial intelligence in management systems, analyzing modern methods of classifying and assessing financial risks using machine learning algorithms, creating an architecture of a decision support system based on predictive models, and evaluating the effectiveness of the developed models based on the results of simulation modeling.

As part of the study, it is necessary to develop a model for forecasting the credit risk of bank customers, which would allow assessing solvency using historical data and modern machine learning methods. The research method includes modeling using machine learning tools, including neural networks and ensemble learning techniques such as Random Forest, as well as data analysis using platforms to visualize results and evaluate the performance of models. Particular attention should be paid to data preparation, selection of appropriate features, evaluation of model accuracy, and construction of interpreted visualizations such as SHAP graphs, ROC curves, etc.

Artificial intelligence is not only a tool for processing large amounts of financial information [2], but also a full-fledged participant in the decision-making process in automated management systems. Thanks to the capabilities of machine learning, neural networks, and other data analysis methods, AI is able to predict, classify, and optimize financial decisions, taking into account a wide range of risks: market, credit, operational, currency, etc.

2. Materials and Methods

Financial risk management is a key area in the activities of financial institutions, banks and corporations. In modern conditions of dynamic market development and high competition, automated financial risk management systems have become an integral part of collecting, processing and analyzing large amounts of data for timely detection of potential threats and decision-making. These systems integrate a variety of tools and technologies, including statistical analysis and modeling techniques, as well as the latest intelligent approaches. In recent years, much attention has been paid to the use of artificial intelligence algorithms, which allow to increase the accuracy of forecasts and the adaptability of systems to changing conditions. Structurally automated control systems of the Russian Federation consist of data collection modules, analytical tools, decision support systems, and monitoring and control modules [11].

The main elements of the classification of financial risks include:

– market risks associated with fluctuations in asset prices, interest rates or exchange rates;
– credit risks arising in the event of insolvency of counterparties;
– operational risks arising from internal failures, errors or fraud;
– liquidity risks associated with the inability to quickly sell assets without significant losses;
– as well as legal and reputational risks arising from non-compliance with regulatory requirements or negative assessment of activities by partners and clients.

Sources of financial risks are divided into external and internal. External factors include economic instability, political changes, natural disasters and market fluctuations that affect the financial performance of the enterprise. Internal sources are related to imperfection of management processes, insufficient control, human error and technological failures.

A systematic approach to risk classification allows you to more effectively identify potential threats and develop adaptive strategies for their neutralization. Thus, financial risks are a complex phenomenon that encompasses various types and sources of uncertainty, and their management requires the use of integrated approaches, including the use of modern automated systems and artificial intelligence technologies to improve the quality of analysis and forecasting of risk factors.

The research method involves modeling using machine learning tools, in particular neural networks and ensemble learning methods such as Random Forest, as well as in data analysis using platforms to visualize results and evaluate the effectiveness of models. Let's consider this issue in more detail.

One of the most common artificial intelligence technologies in the financial sector is machine learning [1]. It allows you to create models that automatically learn from historical data, predict the behavior of financial indicators, identify anomalies and potential risks. In particular, classification and regression techniques are widely used to assess customer creditworthiness, predict exchange rate fluctuations, and detect fraudulent transactions [9]. Another important technology is deep learning, which is based on multi-layered neural networks. They are able to work with unstructured data, such as text information, images, or sound signals, which expands the capabilities of automatic analysis of financial documents, news feeds, and social networks to assess market trends [10]. Another important technology is deep learning, which is based on multilayered neural networks. They are capable of working with unstructured data, such as text information, images, or audio signals, which expands the capabilities of automatic analysis of financial documents, news feeds, and social networks to assess market trends [10].

Natural Language Processing (NLP) technologies are used to automatically analyze and analyze textual information, including news, financial reports, and legislative documents. Thanks to NLP, you can quickly draw conclusions about potential changes in the market, identify risks related to reputation or regulatory requirements. Robotic process automation (RPA) combined with artificial intelligence allows you to optimize routine operations such as transaction processing, reporting, compliance monitoring, which significantly reduces time and reduces the human factor in risk management processes. Financial risk management also benefits from the application of AI-powered decision support systems that integrate real-time analytics, simulate different scenarios, and provide guidance for management. So, to better understand the impact of the use of artificial intelligence on financial risk management, it is advisable to summarize the main aspects that determine the role of AI in this context. The use of modern technologies in the financial sector can significantly reduce various risks, optimize processes and increase the efficiency of institutions. Since each of the types of financial risks has specific characteristics depending on the field of activity, it is important to outline the impact of artificial intelligence technologies on the management of these risks. Table 1 shows the main areas of use of artificial intelligence for financial risk management.

Thus, artificial intelligence technologies in the financial sector create new opportunities to improve the efficiency of financial risk management, automate analytical processes, and adaptively respond to external and internal threats, which confirms their important role in modern automated management systems. To adequately assess the impact of artificial intelligence on the financial sector, it is necessary to take into account both its innovation potential and the possible risks it can cause. Only by applying a balanced approach to the use of this technology, it is possible to integrate it into financial processes as efficiently as possible, providing both economic benefits and maintaining the security and stability of the financial system. Despite the significant benefits of using artificial intelligence in the financial sector, the adoption of these technologies comes with certain risks. Process automation, algorithm-based decision-making, and the use of large amounts of data can pose threats to both banks and insurance companies. In particular,

Table 1

The impact of the use of artificial intelligence on financial risk management

Name	The impact of using AI
Credit risk management	AI makes it possible to more accurately assess customer creditworthiness, reducing the risk of non-payments and unpredictable financial losses
Fraud risks	Application of algorithms to detect anomalies and prevent fraudulent transactions, which reduces possible financial losses
Investment risks	Using AI to Predict Market Fluctuations and Analyze Investment Opportunities
Regulatory risks	Improving compliance control with AI to analyze and verify compliance with regulatory requirements
Personalization of services	Analysis of individual customer needs to create personalized financial products
Operational risks	Automate and optimize financial operations to reduce human error and errors
Cyber protection and security	Increase financial data protection and protect against cyberattacks with algorithms to detect anomalous activity
Liquidity risks	Forecasting the need for liquid funds and optimizing financial management

there is a risk of technical glitches, fraud, data privacy breaches, and ethical and social issues.

It is important to be aware of these risks in order to ensure the reliable functioning of financial institutions and their effective management. Table 2 below shows the main risks associated with the use of artificial intelligence, as well as their impact on the financial sector.

Financial risk management traditionally includes risk assessment, monitoring and making appropriate management decisions. Artificial intelligence can significantly improve these processes by automating routine tasks, increasing the accuracy of predictions, and reducing the subjectivity of assessments. For example, based on historical data, machine learning models can detect complex dependencies between variables that affect credit, market, or operational risk. A key benefit of AI in risk management is its ability to adapt to changing market conditions. Traditional models usually have a fixed structure and limited retrofit options. Instead, AI systems are able to learn from new data on their own, making them particularly effective in dynamic environments. In addition, thanks to its integration with digital platforms, artificial intelligence can work in real-time, which greatly improves the speed of response to potential threats. In the field of financial analysis, AI also acts as an analytical tool for building forecasting models, analyzing scenarios, detecting fraudulent transactions, and improving the overall level of security of the financial system. It is especially important to use explanatory models (Explainable AI), which allow you to get not only the result, but also understand the logic of decision-making, which is critically important for financial institutions operating in a highly regulated environment.

Overall, the role of artificial intelligence in risk management is to streamline the processes of identifying, evaluating, and responding to financial threats. The use of intelligent algorithms allows you to reduce decision-making time, minimize the impact of the human factor and increase the effectiveness of the risk management system. Machine learning (ML), artificial neural networks (AI), and expert systems are key components of the modern approach to financial risk analysis and management. These technologies make it possible to identify hidden patterns in financial data, predict potential threats, and support decision-making based on large amounts of information [6].

Machine learning is a subfield of artificial intelligence that involves building models capable of learning from historical data without explicit programming logic. In the financial sector, machine learning allows you to simulate the behavior of markets, assess lending risks, detect fraud, and conduct portfolio analysis. The main machine learning methods used in the financial field include regression analysis, decision trees, support vector method, ensemble methods (random forest, gradient increase), clustering (k-means, DB-SCAN), and reinforcement algorithms [8]. Artificial neural networks (SHNMs) are mathematical models inspired by the structure of the human brain that effectively recognize complex patterns in data. In financial applications, SNMs are especially useful for tasks that require a high level of forecasting accuracy, such as assessing a customer's solvency or detecting anomalies in transactions. For the analysis of time series,

Table 2

Risks of Using Artificial Intelligence to Manage Financial Risks

Name	Risk description
Algorithmic errors	Errors in AI models can lead to wrong decisions
Cybersecurity	Threats of cyberattacks and data breaches
Regulatory risks	Lack of clear regulations on the use of AI and the need to adapt algorithms
Operational risks	Failure of automated systems in the process of financial decision-making
Ethical risks	The Impact of Automation on the Labor Market

both classical multilayer perceptrons and deep neural networks (GNM), recurrent networks (RNM, LSTM) are used. Expert systems are software complexes that simulate the process of thinking of an expert in a certain subject area. They are based on a knowledge base (rules, patterns, heuristics) and an inference mechanism that allows you to draw logical conclusions. In financial analysis, expert systems are used to automate decision-making in difficult situations, such as when assessing investment risks or choosing the optimal hedging strategy. The combination of the above technologies provides increased forecasting accuracy, flexibility in adjusting models for specific tasks, and the ability to work with different types of data. Table 3 presents the main characteristics of the comparison of machine learning methods, neural networks and expert systems in the context of financial risk management.

In today's automated financial risk management systems, AI models are increasingly being used to assess and predict risks. Such models have the ability to detect complex patterns in data that are not amenable to traditional analytical analysis and provide flexibility in decision-making based on a variety of scenarios [11]. Forecasting models are based on historical data containing information about previous financial losses, changes in the market situation, credit ratings of customers, macroeconomic indicators, etc. The main task of these models is to build an algorithm that predicts the probability of a risk event with high accuracy. The main types of models used in this context include:

- classification models (e.g. logistic regression, decision trees, SVM) that allow you to determine whether an object belongs to the risk category or not;
- regression models that predict the size of expected financial losses;
- neural networks are universal models that can work in both classification and regression modes;
- combined ensemble models (for example, Random Forest or Gradient Boosting), which increase accuracy by combining the results of several algorithms.

The process of building a model consists of several successive stages, shown in Fig. 1: Data preparation, model selection, training, quality assessment, testing, implementation. Particular attention should be paid to increasing the interpretation of models — the use of tools such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations), which allow you to understand the influence of individual variables on the outcome of the forecast. This model covers the full lifecycle of financial risk analysis — from data collection and pre-processing to risk forecasting and monitoring. The key components are the data filtering and normalization stages, training the model based on previous experience, and integrating the results into the management decision-making process.

Thus, the use of artificial intelligence in financial risk forecasting processes can significantly improve the accuracy of assessments, automate control processes, and respond to potential threats in a timely manner, which is critical in a dynamic financial environment.

Let's consider the basic structure of models for preventing financial risks based on neural networks. Neural network-based financial risk warning models are typical examples of the use of AI technology for risk management. The basis of these models is deep learning architecture, which typically includes layered neural networks such as convolutional neural networks (CNNs), recurrent neural networks (RNMs), or long-term memory networks (LTCs). The principle of model design is to predict future potential financial risks by training patterns and features from a large amount of historical data. The input layer of the model receives multidimensional financial data, including market performance, macroeconomic data, financial statements of companies, etc. Hidden layers are responsible for extracting and transforming features, capable of automatically learning complex nonlinear relationships. The output layer provides risk warning signals or risk probabilities.

The model architecture can be customized to meet specific application scenarios. For example, for time series data, LSTM layers can effectively capture long-term dependencies; For structured data, fully connected layers can learn complex combinations of features. Model design also takes into account attention mechanisms that allow the model to focus on the most relevant information, increasing the accuracy of forecasting. Models typically use a multitasking learning system, predicting multiple risk metrics, which helps improve the model's ability to generalize. To account for the characteristics of high dimensionality and sparseness of financial data, model design includes dimensionality reduction techniques and regularization techniques, such as principal component analysis (PCA) and L1/L2 regularization, to prevent overtraining and increase model robustness [11]. Strategies for training and optimizing neural network-based

Table 3

Comparison table

Method	Scope	Advantages	Limitations
Machine learning	Risk Forecasting, Fraud Detection	Automatic Data Learning, Adaptability	The Need for Quality Data, Black Box
Neural networks	Time series, complex dependencies	High precision, generalizability	Complexity of interpretation, requirements for computing resources
Expert Systems	Risk assessment, decision-making	Interpretation, knowledge-based	Narrowness of the subject area, difficulty in updating knowledge

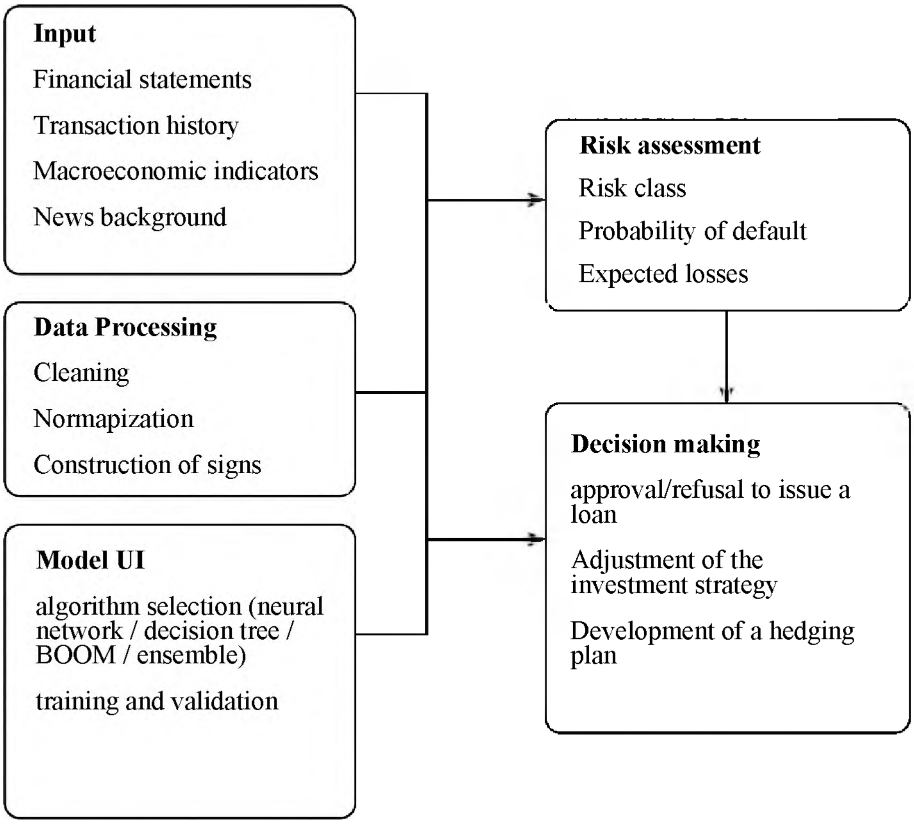

Figura1. Model for forecasting financial risks

financial risk warning models are key steps to ensure model performance. The learning process typically uses supervised learning methods, using labeled historical data as a learning toolkit. The design of the target function of the model should take into account the specifics of financial risk management. For example, asymmetric loss functions can be used to display various costs for missed reports and false alarms. To improve the model's generalization ability, techniques such as cross-validation are commonly used to evaluate model performance, while regularization techniques such as Dropout are used to prevent overtraining. In terms of algorithm selection optimization, adaptive learning speed techniques such as Adam are widely used, which can effectively handle the sparseness and non-stationarity of financial data. Batch normalization methods can accelerate model convergence and improve performance [10].

Model training also faces the problem of sample imbalance, as financial risk events are usually rare in historical data. To solve this problem, methods such as oversampling, undersampling, or generative-adversarial networks (GANs) can be used to balance the sample distribution. Model optimization is an iterative process that involves steps such as feature development, model training, performance evaluation, and parameter adjustments. Expert knowledge can also be incorporated into this process, such as the use of pre-trained word embedding to process text data or the design of specific network structures based on knowledge of the financial field. Therefore, effective model training requires a combination of high-quality data processing, the right choice of optimization algorithms, and deep expertise in the industry. The iterative nature of this process allows us to achieve high forecasting accuracy and adaptability to difficult conditions of financial markets.

Evaluating the model and analyzing the interpretation is a crucial step in ensuring the reliability and effectiveness of financial risk warning models based on neural networks. Evaluation metrics should be chosen based on specific risk management objectives, with commonly used metrics including accuracy, precision, completeness, etc. For financial risk warnings, the timeliness of model warnings and the level of false alarms are especially important. Therefore, time-weighted valuation indicators can be used, or economic costs can be entered as evaluation criteria. The stability and reliability of the model are also important aspects of the evaluation. Competitive random testing or stress testing can be used to evaluate the performance of the model under extreme conditions.

In addition, it is necessary to focus on the model's ability to generalize, and methods such as Rolling Forecast can be used to evaluate the effectiveness of the model in different periods. However, the black-like nature of neural network models creates difficulties for their application in the financial sector, especially in regulatory requirements and risk management practices, where model interpretation is required. To solve this problem, various methods can be applied to improve the interpretation of models. These methods include trait importance analysis, interpretation of SHAP values (Shapley additive explanations), locally interpreted model-agnostic explanations (LIME), etc. [10].

These techniques can help to understand the basis for model decision-making, identify key risk drivers, and provide support for risk management decisions. Visualization techniques are also an effective means of improving model interpretation. For example, the use of heat maps to demonstrate the influence of various features on prediction results, or the use of decision trees to approximate the decision-making process of neural networks. These interpretation analyses not only help to increase the validity of the model, but also provide direction for its further optimization.

3. Results and Discussion

At this stage of the study, the task of forecasting the credit risk of bank customers is formulated, as well as the preparation of an appropriate dataset for training artificial intelligence models. The purpose of modeling is to classify customers based on historical financial indicators into two groups: solvent and potentially problematic. To implement the case, an open dataset from the Kaggle platform was used, which includes variables describing the client's profile: age, income, number of open loans, debt repayment history, the presence of delinquencies, etc. [8]. After uploading the data, pre-processing was carried out: clearing duplicates, excluding missing values, converting categorical variables to numerical ones (one-hot coding), as well as normalizing numerical features. Visual analysis of the data was also carried out to detect anomalies and distribution by class. Correlation analysis made it possible to establish the most influential variables for modeling, such as the history of delinquencies and the debt ratio. As a result of the training, a training sample was formed, suitable for further use in machine learning [9].

Within the framework of the study, a practical case of building a model for forecasting the credit risk of bank customers was implemented. The main goal is to create an intelligent classification system capable of determining whether the client will be able to service the loan in a timely manner in the future. Such a system allows the bank to reduce the likelihood of losses due to non-repayment of loans, increase the efficiency of risk management and make informed credit decisions. For the simulation, an open dataset from the Kaggle platform — Home Credit Default Risk — was used. This dataset contains more than 300,000 customer records with various characteristics such as age, income level, number of dependents, credit history, type of housing, employment, etc. The first step was to clean and transform the data. A significant number of missing values were identified and removed in categories where the complement is inappropriate. Numerical features were normalized using a mini-max scale. Categorical variables are encoded in one-hot encoding for compatibility with machine learning algorithms. Sample balancing was also carried out using the SMOTE method to eliminate the imbalance between classes (solvent and insolvent clients). Table 3 describes the main variables chosen to build the model.

For comparison, two models were created: Random Forest Classifier as a basic neural network (ANN) and an artificial neural network (ANN) as a more complex variant based on Tensor-Flow/Keras. Random Forest provides interpretation, while the neural network is able to detect nonlinear dependencies in data more deeply. A random forest provides interpretation, while a neural network is able to detect nonlinear dependencies in data more deeply. Both models are trained on 80% of the data, 20% is reserved for test sampling. For the neural network, an architecture with three hidden layers, ReLU activation, and an output layer with the softmax function was used. Adam was used as an optimizer. Dropout is used to prevent overtraining. After training the model, a comparative analysis of the results was carried out according to key metrics: accuracy, completeness, F1 balance. Below is a comparative table of models (Table 5).

As can be seen from Table 5, the random forest model showed the highest accuracy and an F1 score, showing a good balance between completeness and accuracy. The neural network also showed high performance, somewhat inferior to the decision tree. This shows the potential of using AI models to effectively identify financial risks based on historical customer data. To improve the interpretation of the model, SHAP (Shapley Additive Explanations) techniques have been applied, which allow you to determine which variables most influence the model's decisions. The

Table 4

Main variables for building a model

Variable Name Description Variable Type	Variable Name Description Variable Type	Variable Name Description Variable Type
AMT_INCOME_TOTAL	Total Client Revenue	Numeric
AMT_CREDIT	Amount of Requested Loan	Numeric
DAYS_EMPLOYED	Duration of employment (in days)	Numeric
NAME_HOUSING_TYPE	Housing type	
TARGET	Target variable (0 is good, 1 is risk)	Binary
CNT_CHILDREN		Number of dependents
NAME_EDUCATION_TYPE	Client's level of education	

Table 5

Comparison of models by main metrics

Metrics	Logistic Regression	Random Forest	Logistic Regression
Accuracy	0.76	0.84	0.81
Povnota	0.69	0.80	0.77
F1-Ball	0.72	0.82	0.79

SHAP analysis showed that the key factors were the client's income, age, and length of service. Fig. 2 shows a graph in the form of a SHAP scatter chart.

After training the neural network model to classify the client's credit risk, an important step is to interpret its results. Interpretation is a critical characteristic for the banking sector, where it is necessary not only to provide a forecast, but also to explain the reasons for the decision. One of the most effective approaches to interpretation is the use of SHAP (SHapley Additive Explanations), a method based on game theory that allows you to quantify the contribution of each feature to the model solution.

SHAP values demonstrate which customer characteristics (income, age, debt, number of open loans, etc.) had the greatest impact on the final decision — whether to classify the customer as reliable or risky. Figure 1 presented earlier shows a generalized summary graph of SHAP. It depicts the top 10 traits that most affect the model's results. Red dots indicate high values of the trait, blue dots indicate low values. For example, a high level of indebtedness has a positive SHAP value, indicating an increase in the likelihood of classifying a client as risky. Visualization of the SHAP study allows us to draw several important conclusions:

- the key risk factors were signs related to the level of income, the history of overdue payments and the number of open loans;
- the model demonstrates logical behavior, since a high financial burden or unstable payments really increase credit risk;
- The positive point is that the impact of the signs meets the expectations of financial experts, that is, the model is not only accurate, but also understandable.

For the in-depth analysis, the error matrix (confusion matrix) depicted in Table 5 was also used, which showed that the model has a high sensitivity to identifying risky clients, i.e. most potentially dangerous applications were identified correctly.

After training the neural network model to classify the client's credit risk, an important step is to interpret its results. Interpretation is a critical characteristic for the banking sector, where it is necessary not only to provide a forecast, but also to explain the reasons for the decision. One of the most effective approaches to interpretation is the use of SHAP (SHapley Additive Explanations), a method based on game theory that allows you to quantify the contribution of each feature to the model solution. SHAP values demonstrate which customer characteristics (income, age, debt, number of open loans, etc.) had the greatest impact on the final decision — whether to classify the customer as reliable or risky.

Figure 1 presented earlier shows a generalized summary graph of SHAP. It depicts the top 10 traits that most affect the model's results. Red dots indicate high values of the trait, blue dots indicate low values.

For example, a high level of indebtedness has a positive SHAP value, indicating an increase in the likelihood of classifying a client as risky. Visualization of the SHAP study allows us to draw several important conclusions:

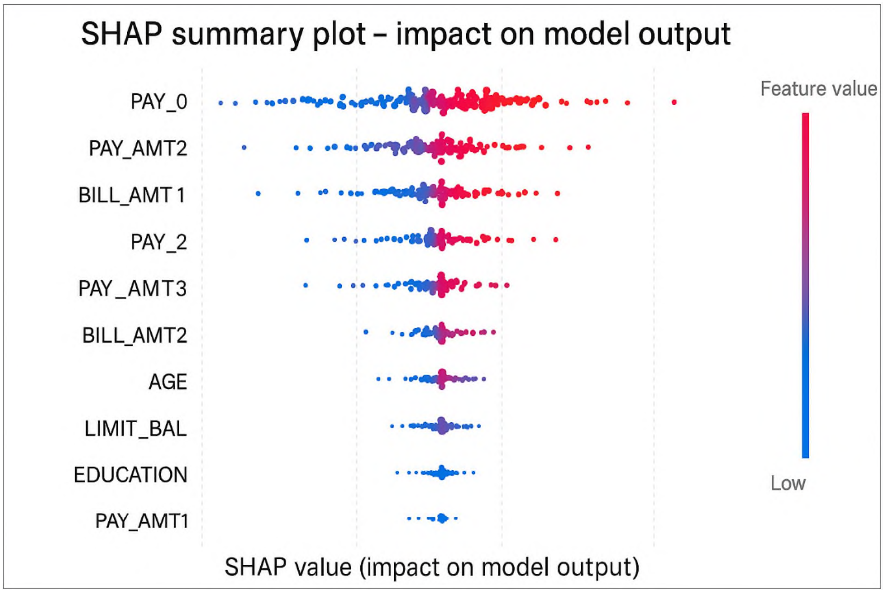

Figure 2. Graph of the influence of signs on the forecast

Table 6

Error matrix for a neural network

	Forecast: Reliable	Forecast: Risky
Fact: Reliable	321	45
Fact: Risky	28	106

– the key risk factors were signs related to the level of income, the history of overdue payments and the number of open loans;
– the model demonstrates logical behavior, since a high financial burden or unstable payments really increase credit risk;
– The positive point is that the impact of the signs meets the expectations of financial experts, that is, the model is not only accurate, but also understandable.

For the in-depth analysis, the error matrix (confusion matrix) depicted in Table 6 was also used, which showed that the model has a high sensitivity to identifying risky clients, that is, most potentially dangerous applications were identified correctly.

Based on this table, key indicators can be calculated: accuracy 84.8%; completeness 79.1%; F1 indicator: 74.4%. These values indicate a fairly high quality of the model, especially considering that in risk management tasks it is more important to minimize false negative results (i.e. not to miss a risky client).

In addition, the ROC curve shown in Fig. 2, demonstrates the relationship between sensitivity (level of true positive results) and specificity (level of false positives) of the model. The area under the curve (AUC) was 0.89, indicating the model's high discriminatory capacity.

Therefore, the use of SHAP analysis, error matrix, and ROC curve allows not only to assess the accuracy of the model, but also to make it transparent to financial analysts and regulators. This is important for making informed management decisions in the banking sector.

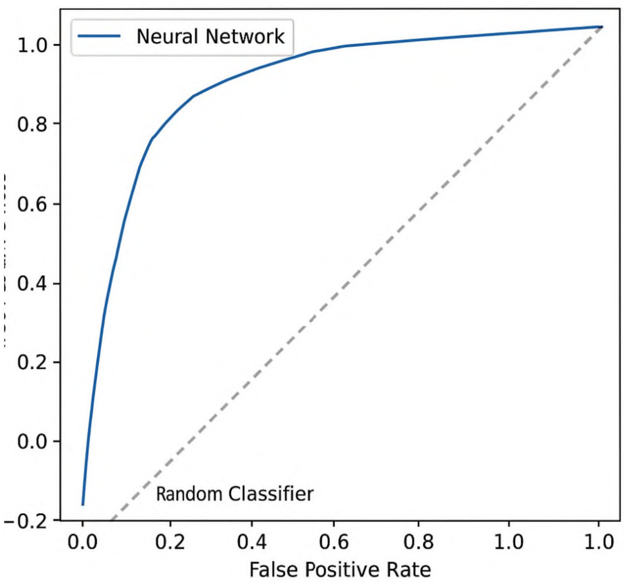

Figure 3. ROC curve of a neural network

4. Conclusions

In the course of the study, the opportunities, advantages and problems of using artificial intelligence in automated financial risk management systems were analyzed. The main attention was paid to the analysis of theoretical foundations, classification of financial risks, technical features of the implementation of intelligent systems, as well as practical modeling on the example of forecasting credit risks. General approaches to financial risk management are considered, their classification and features in modern economic conditions are determined.

The basic principles of building automated financial risk management systems are analyzed and the feasibility of introducing intelligent methods, in particular machine learning and neural networks, into financial analytics is substantiated.

A study of modern methods of artificial intelligence used for risk analysis and forecasting has been carried out. The features of deep learning models, decision trees, ensemble methods, as well as criteria for evaluating their effectiveness are considered. Particular attention is paid to the interpretation of models, which is an important factor for the implementation of AI in risk management practices in accordance with regulatory requirements.

A practical case was implemented to build a model for forecasting the credit risk of a bank client. Real data was pre-processed, several models were built and tested (random forest, neural network), and accuracy was estimated using metrics such as F1 score and ROC curve. In addition, the analysis of the importance of features using SHAP graphs is carried out and the architecture of the system that can be used to integrate such a model into a practical automated control system is substantiated.

In general, the results of the work confirm the high efficiency of using artificial intelligence methods for automated analysis and forecasting of financial risks. Such models can not only improve the accuracy of risk identification, but also ensure the efficiency of decision-making in financial institutions. At the same time, their implementation requires proper technical and organizational support, including the issues of interpretation, validation and adaptation to changes in the market environment.

ADDITIONAL INFORMATION

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CONFLICT OF INTEREST
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ШТУЧНИЙ ІНТЕЛЕКТ В АВТОМАТИЗОВАНИХ СИСТЕМАХ УПРАВЛІННЯ ФІНАНСОВИМИ РИЗИКАМИ

Анотація. *Метою представленої статті є дослідження застосування штучного інтелекту в автоматизованих системах управління фінансовими ризиками для підвищення точності, оперативності та ефективності прийняття управлінських рішень у фінансовій сфері. Дослідження полягає у комплексному вивченні теоретичних і методичних основ застосування штучного інтелекту в системах управління, аналізу сучасних підходів до класифікації та оцінки фінансових ризиків із використанням алгоритмів машинного навчання, формуванні архітектури системи підтримки прийняття рішень на основі моделей прогнозування, а також оцінці ефективності побудованих моделей за результатами симуляційного моделювання. У межах проведеного дослідження розроблено модель прогнозування кредитного ризику клієнтів банку, яка дозволяє здійснювати оцінку платоспроможності на основі історичних даних та сучасних методів машинного навчання. Методом дослідження є моделювання за допомогою інструментів машинного навчання, зокрема нейронних мереж і методів ансамблевого навчання (Random Forest), а також аналізування даних із використанням платформ для візуалізації результатів і оцінки ефективності моделей. Особливу увагу приділено підготовці даних, вибору релевантних ознак, оцінці точності моделей та побудові інтерпретованих візуалізацій, таких як SHAP-графіки, ROC-криві тощо. Результатом проведеного дослідження стало створення ефективної моделі прогнозування кредитного ризику, яка демонструє достатньо високий рівень точності класифікації та здатність до адаптації при зміні вхідних умов. Практичне значення дослідження полягає у можливості впровадження розробленої моделі до існуючих автоматизованих систем управління фінансовими ризиками банківських установ, що дозволить зменшити рівень кредитних втрат, підвищити фінансову стабільність і забезпечити більш точне управління ризиками. Такий підхід сприяє розвитку інтелектуальних фінансових систем, підвищенню рівня автоматизації управлінських рішень та зміцненню конкурентоспроможності фінансових установ у сучасних ринкових умовах.*

Ключові слова*: штучний інтелект, фінансові ризики, машинне навчання, кредитний ризик, нейронні мережі, автоматизована система управління, прогнозування, класифікація.*

НАУКОВИЙ ЖУРНАЛ

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