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КРЕАТИВНІ ПІДХОДИ У СУЧАСНИХ НАУКОВИХ ДОСЛІДЖЕННЯХ

Монографія

CREATIVE APPROACHES TO CONTEMPORARY RESEARCH

Monograph

2026

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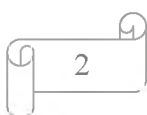
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ОБИРАЙТЕ ПЕРШИХ! ДОВІРЯЙТЕ СПРАВЖНІМ! ЦІНУЙТЕ УНІКАЛЬНІСТЬ!

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2.3. Application of artificial intelligence in automated management systems of financial institutions

The modern financial system operates in conditions of significant uncertainty, digital transformation and growing data volumes. For banks and financial institutions, reliable financial risk management is becoming a key task, which requires the introduction of intelligent data analysis and forecasting technologies. One of the most promising areas for solving the problem is the use of artificial intelligence technologies that can automate risk assessment, find anomalies and increase the accuracy of management decisions. A conceptual architecture of an intelligent analytical system has been developed that integrates machine learning algorithms to assess customer creditworthiness and identify potential defaults. The object of the study is automated systems for managing financial risks of banking institutions. The subject of the study is algorithms, models and methods of artificial intelligence used to analyze, forecast and minimize financial risks. The paper analyzes modern approaches to the use of ensemble methods and deep neural networks to build risk assessment models. Experimental modeling based on the generated data was carried out, which confirmed the forecasting accuracy of more than 85%, which indicates the effectiveness of integrating AI models into financial ICS. The results of the study prove that the introduction of intelligent algorithms in banking systems allows to increase the accuracy of risk assessment, reduce decision-making time and ensure the adaptability of analytical models to changes in the external environment. The practical value of the work lies in the possibility of using the developed model as a basis for building an intelligent risk management module in domestic banks. Keywords: machine learning, neural networks, automated control system, data processing, modeling, forecasting, classification.

Introduction. The modern financial system operates in conditions of high uncertainty, digital transformation and growth in data volumes. For banks and financial institutions, effective financial risk management becomes a key task, which requires the introduction of intelligent data analysis and forecasting technologies. One of the most promising areas is the use of artificial intelligence technologies that can automate risk assessment, identify anomalies and increase the accuracy of management decisions.

Artificial intelligence is increasingly being integrated into automated management systems, providing fast data processing, deep analytics, and adaptive decision-making. Machine learning algorithms such as XGBoost, Random Forest, and neural networks (CNN) are successfully used in predicting credit risk, monitoring transactions, and fraud prevention. Of particular interest are Explainable AI (explainable AI) models, which increase transparency and trust in automated decisions.

The term financial risks (FR) refer to the possibility of losses or adverse financial consequences as a result of uncertainty and fluctuations in the financial environment. Financial risks are an integral part of the operations of any enterprise or financial institution, and their effective management is key to ensuring stability and profitability.

The main goal of financial risk management is to timely identify, assess and minimize possible threats, which allows you to make informed decisions to preserve capital and maintain financial stability.

The classification of financial risks is a key stage in building a system for their management, as it allows you to formalize the approach to their identification, assessment and monitoring. Depending on the source of occurrence and the nature of the impact, the scientific literature distinguishes several main groups of risks: credit, market, operational, liquidity risks and systemic risks. Each of these categories has its own characteristics, formation mechanisms and control tools.

The main categories of financial risks include:

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

Credit risk is one of the most common types of financial risk and characterizes the possibility of a borrower's failure to fulfill its financial obligations. It arises in the process of lending, investing, or other financial transactions related to the provision of funds under certain repayment conditions. The sources of credit risk are a decrease in the

At the same time, the article [3] highlights an important problem of FR management, when commodity, financial, information and labor markets are combined. A methodological system for the formation of RF management plans is presented, which includes the following steps: identification of threats, their calculation, formation and implementation of effective plans, as well as monitoring and updating. The proposed methodology takes into account the need for a systematic approach to the management of the Federal Reserve with a view to the inclusion of enterprises in foreign economic processes.

In this aspect, the study [4] aims to consider the potential of using AI to improve the accuracy of prediction, detect fraudulent schemes, and improve the management of credit and insurance hazards.

The article applies an approach that involves a statistical method for calculating the effectiveness of the use of artificial intelligence in the management of digital media, as well as methods of comparative analysis to find out the advantages and disadvantages of AI in relation to traditional control systems. Practical cases and analysis of the activities of leading banks and insurance institutions made it possible to demonstrate the real possibilities of using AI in the financial environment.

Considerable attention in the research [5] is devoted to studying the analysis of the current state of AI adoption in the financial sector, assessing the regulatory challenges accompanying this process, as well as studying the potential for further growth of this technology to ensure the sustainability of economic growth and innovations in the financial industry.

Problem analysis and task setting. The study is aimed at studying the effectiveness and potential of using AI in automated financial risk management systems, creating an analytical model for risk prediction based on the latest machine learning algorithms, as well as developing a conceptual architecture of an intelligent analytical system that combines machine learning algorithms to assess customer creditworthiness and identify possible defaults using data mining.

Research methods include modeling using machine learning tools, including neural networks and ensemble learning methods; data analysis using platforms to visualize results and evaluate the performance of models.

The purpose of the study is automated financial risk management systems for banking institutions. The subject of the research is artificial intelligence algorithms, models, and techniques used to analyze, predict, and minimize financial risks.

Research objectives:

- to review general approaches to financial risk management;
- to establish their classification and features in modern economic conditions;
- to analyze the main principles of building an automated control system and to confirm the feasibility of introducing intelligent methods;
- to conduct a detailed study of modern AI methods used to analyze and predict risks;
- to consider the features of deep learning models, decision trees, ensemble methods, as well as criteria for evaluating their effectiveness;
- to implement a practical case for building a model for predicting the credit risk of a bank client;
- to conduct preliminary processing of valid data;
- to build and test several models for predicting credit risk;
- to assess the accuracy of predicting credit risk using metrics; confirm the architecture of the system, which can be used to integrate such a model into a practical ICS.

Structurally, ICS contains data collection modules, analytical tools, decision support systems, and supervision and control modules [5]. A systematic approach to the classification of RF allows you to more successfully identify potential threats and develop flexible strategies for their elimination.

Results. The research methodology involves modeling using machine learning (ML) tools, in particular neural networks (NM) and ensemble mixing methods. One of the most common AI technologies in the financial sector is NM [1]. It allows you to create models that automatically gain knowledge, predict the behavior of financial indicators, identify inconsistencies and potential dangers.

An important technology is deep learning, which relies on multi-layered NMs. Despite the high potential of artificial intelligence in the field of financial risk management, the process of its implementation is accompanied by a number of complex challenges.

They are interdisciplinary in nature and cover technical, regulatory, ethical, cybersecurity and socio-economic aspects. Each of them has a significant impact on the validity, trust and security of the use of intelligent technologies in the financial sector. It is important to understand these risks in order to ensure the stable functioning of financial institutions and their effective management.

The management of the Federal Reserve includes threat assessment, supervision and implementation of relevant management decisions. AI can significantly improve these processes by automating routine tasks, increasing the accuracy of predictions, and reducing the subjectivity of assessments.

Traditional models usually have an unchanged structure and limited room for improvement. Instead, AI systems are able to learn from new data on their own, which makes them especially effective in changing environments. The threat is the ability of AI systems to adapt to changing market conditions.

Thanks to integration with digital platforms, AI can operate in real time, which significantly improves the speed of response to potential dangers. In general, the role of AI in the management of FI is to optimize 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.

In Table 1 shows the main uses of AI for the control of the PH.

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
Investment 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

In Table 2 shows the main dangers associated with the use of AI and its impact on the financial sector.

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

Thus, artificial intelligence technologies in the financial sector create new opportunities for improving the efficiency of financial risk management, automation of analytical processes and adaptive response to external and internal threats, which confirms their important role in modern automated management systems.

The use of AI technologies in the field of financial risk management has become one of the key trends in the transformation of banking systems and financial markets in the world. Leading international banks and financial organizations are actively implementing algorithms of machine learning, deep learning, natural language processing and other intelligent technologies to increase the accuracy of risk forecasting, optimize decision-making and reduce analytics costs. Based on the analysis of practical cases, it is possible to trace a significant difference between the approaches of global and Ukrainian financial institutions, which is due to both the level of technological development and the regulatory and economic environment.

Global experience in the use of AI in financial risk management. One of the most famous examples of the integration of AI into financial activities is JPMorgan Chase & Co. This institution has implemented a comprehensive analytical board form based on ML algorithms, which allows you to predict credit risk and detect potentially fraudulent transactions. In particular, the COiN (Contract Intelli-gence) system analyzes legal documents and loan agreements using natural language processing (NLP) technologies. This made it possible to reduce the time of contract verification from 360 thousand hours of manual labor to a few seconds. In the field of risk management, this provides quick identification of risky provisions in contracts and minimizes legal losses.

In addition, JPMorgan uses neural networks to detect fraudulent transactions, combining historical transaction data, customer behavioral patterns, and external macroeconomic indicators. Algorithms analyze thousands of parameters in real time, which allows you to prevent fraud and reduce operational risks.

HSBC Bank, one of the largest banks in Europe, actively uses deep learning systems to combat money laundering (AML) and monitor transactions.

One of the most successful solutions was the AI-driven Risk Advisory project, which uses machine learning to monitor liquidity risks and market fluctuations. The system analyzes more than 100,000 daily transactions, predicts possible risk scenarios based on historical data, and offers recommendations for financial analysts. As a result, HSBC was able to reduce manual risk analysis by 40% and improve the accuracy of market forecasts by up to 92%.

Another example is Citibank, which introduced the "AI Credit Risk Engine" system, a platform that uses deep neural networks (DNNs) to assess the creditworthiness of borrowers. The algorithm is able to take into account non-standard indicators, such as transactional behavior, the frequency of changes in financial habits, or even semantic analysis of customer request texts. This allowed the bank to reduce the rate of credit defaults by 18% in the first year after the system was implemented.

Thus, global practice demonstrates that the use of AI allows financial organizations not only to reduce losses from risky operations, but also to create flexible, adaptive management systems that self-learn and improve their forecasts in real time.

Ukrainian experience in the use of AI in financial risk management. In Ukraine, the process of digitalization of the financial sector is actively developing, although the level of AI use has not yet reached global proportions. However, recent years have shown significant shifts in the implementation of intelligent risk analysis systems in leading banks and regulatory structures. The most active use of AI technologies is PrivatBank, Oschadbank, and the National Bank of Ukraine (NBU).

PrivatBank, as the largest bank in Ukraine, was one of the first to use machine learning algorithms to analyze credit risks and detect fraudulent transactions. The system automatically analyzes customer behavioral patterns – payment times, types of purchases, geolocation data – and generates dynamic risk profiles. As a result, the number of illegally approved transactions decreased by more than 30%. The bank also implements elements of predictive analytics to assess the creditworthiness of small business customers using data from open sources (Open Data, transaction analytics, data from tax registers).

Sberbank of Ukraine uses elements of artificial intelligence in the process of assessing credit risks of individuals and small businesses. The main goal is to reduce decision-making time and increase the accuracy of assessment. Algorithms analyze both financial indicators and behavioral characteristics of customers (for example, the history of interaction with the bank, the level of activity in online banking, the average volume of transactions). Such systems form personalized loan offers, optimizing the risk of default.

The National Bank of Ukraine (NBU), as part of the program of digital transformation of the financial sector, is also exploring the possibilities of using AI to monitor systemic risks. In particular, the NBU implements analytical tools for forecasting macroeconomic indicators, analyzing currency fluctuations, and stress testing banks. Machine learning models allow identifying potential liquidity risks and improving the accuracy of economic forecasts.

Comparative analysis of global and Ukrainian experience. Comparative analysis shows that the main difference between global and Ukrainian practices lies in the scale of AI use, the level of automation, and data availability. While international banks integrate AI into all key risk management processes (from liquidity forecasting to dynamic portfolio analysis), Ukrainian institutions focus mainly on fraud, scoring, and credit risk detection.

Limited access to large, structured data sets remains an important challenge for Ukraine. For the effective operation of AI models, high quality, completeness, and historicity of financial information are required, which is currently a problematic aspect. There is also a shortage of specialists in the field of data science and financial analytics, which complicates the large-scale implementation of intelligent systems.

Despite this, the Ukrainian financial ecosystem demonstrates positive dynamics, especially due to the development of open banking, fintech startups, and initiatives by the regulator. The integration of AI into banking processes today can significantly increase the efficiency of risk management, and in the future, create conditions for the formation of a national intelligent risk management platform.

Thus, the analysis of global and Ukrainian experience shows that the use of AI in the field of financial risk management is not only a technological trend, but a strategic necessity. Global financial leaders demonstrate the deep integration of intelligent systems into decision-making processes, while Ukrainian banks are just beginning this path. The main areas of development are improving the quality of data, developing local research centers on AI in finance, as well as forming a regulatory framework for the safe use of artificial intelligence in the financial sector.

Table 3 provides a comparative analysis of the experience of using AI technologies in Ukrainian and global banks.

Table 3

Comparison of global and Ukrainian experience in the use of AI in financial risk management

Criterion	World practice	Ukrainian practice
AI adoption rate	High: integration into core business processes, automated risk management systems	Medium: implementation of separate AI modules for scoring and monitoring transactions
Main areas of application	Credit Risks, Market Risks, Liquidity, Operational Risks, Systemic Risks	Credit scoring, fraud, operational risks, customer data analytics
Technological tools	Deep Neural Networks (DNN), NLP, reinforcement learning	Machine learning (supervised), clustering
Level of automation	Level of automation	Partial automation, the analyst confirms the system's decision
Data Sources	Internal + Open Data, Big Data Funnels, Integration with Global Information Flows	Limited Data, Mostly Internal, Partial Use of Open Data
Implementation results	Reducing the level of defaults, optimizing risk models, saving time and resources	Improving scoring accuracy, reducing fraud, forming a basis for further development

Challenges and challenges of implementing AI in risk management. Despite the high potential of artificial intelligence in the field of financial risk management, the process of its implementation is accompanied by a number of complex challenges. They are interdisciplinary in nature and cover technical, regulatory, ethical, cybersecurity and socio-economic dimensions. Each of them significantly affects the efficiency, trust and safety of the use of intellectual technologies in the financial sector.

Technical challenges. One of the key technical issues is the quality and availability of data. Machine learning algorithms require large amounts of reliable, representative information. In reality, financial institutions are often faced with the lack of structured historical data, their incompleteness or distortion. For example, client data may contain errors, outdated records, or be incomplete due to privacy concerns. This directly affects the accuracy of AI models, which can lead to wrong decisions, especially in the field of credit scoring or default forecasting.

Another aspect is the interpretation of models. Complex neural networks (especially deep ones) function as "black boxes" – they can provide accurate predictions, but it is often impossible to explain why a certain decision was made. This creates a problem of confidence in the results of the model on the part of regulators, auditors and customers.

Also, the integration of AI models into existing risk management systems remains a technical challenge. Many banks and financial institutions have outdated IT infrastructures built on traditional databases and statistical analysis algorithms. Integrating modern AI solutions requires significant resources, both financial and human.

Regulatory challenges. The regulatory environment for AI in the financial sector has not yet been fully formed. Most countries lack specific standards on how AI models should work, what are the requirements for their transparency, testing, validation and accountability in case of error. Ukraine also has an insufficient regulatory framework in the field of AI. Although the National Bank of Ukraine actively supports the digitalization of the financial sector, the legal norms governing the use of automated decision-making systems remain fragmented. This poses risks for banks, which may be accused of discriminating against customers or violating data privacy. Particular attention needs to be paid to harmonizing the requirements of the GDPR (General Data Protection Regulation) with machine learning practices, since the latter often uses personal data to train models.

Ethical challenges. Ethical issues in the use of AI are closely related to issues of fairness, transparency, and accountability. If the algorithm is trained on historical data in which there are hidden biases (for example, social or gender), it can reproduce or even reinforce them. This can lead to discriminatory decisions in credit scoring or in the assessment of the risk of default.

Another important ethical issue is responsibility for decisions made by AI. If an automated system misclassifies risk and causes financial losses, the question arises: who is responsible – the developer, the bank, or the algorithm itself.

Cybersecurity challenges. The financial sector is one of the most attractive targets for cybercriminals, so the adoption of AI poses new security challenges. Machine learning algorithms can be vulnerable to "adversarial attacks" – specially crafted changes in input data that lead to flawed model decisions. For example, a slight modification of the data can cause the algorithm to misestimate the creditworthiness of the customer. The risk of misuse of AI models also increases – a fraudster can use open models or tools to predict market behavior in their own interests.

Socio-economic challenges. The introduction of AI in the financial sector can have an ambivalent impact on the labor market. On the one hand, process automation allows you to reduce costs and increase efficiency. On the other hand, there is a risk of job cuts, especially among employees who perform analytical or administrative functions. At the same time, there is a growing demand for specialists in data science, data analytics, cybersecurity, and AI ethics. Generalized problems and possible ways to overcome them are presented in Table 4.

Table 4

The main problems in the implementation of the financial risk management system

Problem category	Essence of the challenge	Potential consequences	Possible solutions
Technical	Poor or no data quality	Reduced accuracy of forecasts	Creation of unified databases
Regulatory	Lack of clear standards for the use of AI in finance	Legal risks, lack of customer trust	Development of regulations; international harmonization of rules
Ethical	Data bias, lack of transparency of models	Customer discrimination, damage to the bank's reputation	Audit of algorithms; ethical codes for the use of AI
Socio-economic	Automation replaces part of the workforce	Unemployment, social tension	Retraining of personnel; creation of new professions in the field of AI
Cybersecurity	Vulnerability of models to attacks and data breaches	Financial losses, reputational losses	Use of secure environments; regular monitoring of models

The analysis shows that the implementation of artificial intelligence technologies in financial risk management systems is accompanied by a number of complex challenges that cover technical, regulatory, ethical, cybersecurity, and socio-economic aspects. Despite the obvious advantages – increasing the accuracy of forecasting, the speed of data processing and reducing the human factor – the effective use of AI in the financial sector is impossible without a comprehensive approach to overcoming these problems.

Technical difficulties related to data quality and model transparency require the implementation of data management policies and the development of explainable AI methods. Regulatory challenges require the creation of a clear regulatory framework that would define the requirements for the use of AI algorithms in financial activities, ensuring a balance between innovation and consumer protection.

Ethical aspects related to fairness, non-discrimination and responsibility for decisions made by algorithms remain equally important. Cybersecurity risks require an increase in the level of protection of IT infrastructures, and socio-economic consequences require the development of state programs for retraining personnel and stimulating the development of new professions in the field of analytics and artificial intelligence.

Thus, the successful implementation of AI in financial risk management is possible only if all the above factors are taken into account in a comprehensive manner. This requires not only technological innovation, but also strategic vision, interdisciplinary cooperation, and responsible policies on the part of the state, business, and the scientific community.

NMs, artificial neural networks (AIs), and expert systems are key components of the modern approach to FR analysis and management. These technologies make it possible to find hidden patterns in financial data, predict possible threats, and facilitate the decision-making process based on large amounts of information [4]. The main methods of NM used in the financial industry include regression analysis, tree structures, the method of reference vectors, ensemble methods, grouping and reinforcement algorithms [5].

In financial analysis, expert systems are used to automate decision-making in difficult circumstances, in particular when determining investment risks or selecting the best hedging strategy. Setting up hyperparameters is a key step in creating effective machine learning models, which avoids overfitting and improves accuracy.

In Table 5 shows a comparison of the methods of NM and expert systems in the field of RF management.

Table 5

Comparison of methods in the context of FR management

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

The combination of these technologies provides improved quality of forecasting, adaptability in the formation of models for certain tasks and the ability to operate with heterogeneous information.

The main types of models used in this context are:

- classification models, which make it possible to find out whether an object belongs to a risk group or not;
- regression models that predict the amount of expected financial losses; neural networks are universal models capable of functioning in both classification and regression modes;
- consolidated ensemble models that improve accuracy by combining the inferences of multiple algorithms.

Creating a model contains several sequential steps, shown in Fig. 1

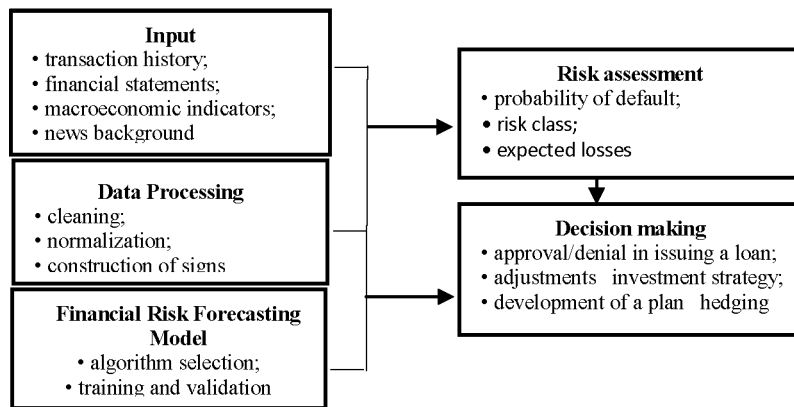


Fig. 1. Financial Risk Forecasting Model

This model covers the entire life cycle of RF assessment – from data collection and preliminary processing to risk forecasting and supervision.

The use of AI in the processes of predicting FR significantly increases the accuracy of assessments, visualizes surveillance processes and responds to possible risks in advance. Model training is confronted with the issue of sample disequilibrium. To remove this obstacle, it is possible to use approaches such as oversampling, undersampling or generative-adversarial networks to equalize the distribution of the sample.

Model refinement is an iterative process that encompasses steps such as feature creation, model training, performance weighting, and hyperparameter changes. It is also allowed to integrate professional knowledge into this process, for example, the use of pre-trained word embeddings to process textual information or the design of specific network structures taking into account financial awareness.

Effective model training requires a combination of high-quality data processing, the right choice of optimization algorithms, and deep expertise in the field. Model evaluation and interpretation analysis is a crucial step in ensuring the reliability and effectiveness of MN-based FR warning samples.

Evaluation metrics are selected based on specific goals of FR management, with commonly used indicators including accuracy, precision, completeness, etc. Evaluating the effectiveness of artificial intelligence models is one of the key stages in building financial risk forecasting systems.

It allows not only to determine how well the model recognizes patterns in historical data, but also to assess its ability to adequately respond to new situations in the financial environment. To do this, a set of performance metrics is used, which quantify the accuracy of predictions, as well as explanatory artificial intelligence (XAI) methods aimed at interpreting the work of models.

A summary comparison of the main performance metrics is given in Table 6.

Table 6

Key Metrics for Evaluating the Quality of ML Models

Metric	Formula	Interpretation	Optimal Value
Accuracy	$(TP+TN)/(TP+TN+FP+FN)$	Proportion of correct predictions	Approaching 1
Precision	$TP/(TP+FP)$	How many predicted risks turned out to be real	Approaching 1
Recall	$TP/(TP+FN)$	Share of Real Risks Found	Approaching 1
F1-score	$2 \times (Precision \times Recall) / (Precision + Recall)$	Balance between accuracy and completeness	Approaching 1

The task of modeling is to classify clients based on historical financial indicators into two groups: solvent and potentially dysfunctional. An open dataset from the Kaggle platform was used, which contains variables describing the client's profile: age, income, number of open loans, debt repayment history, the presence of delinquencies, etc. [4]. After loading the data, the initial processing was carried out:

- cleaning duplicates;
- excluding missing values;
- converting categorical variables into numerical ones (one-hot coding), as well as normalizing numerical features.

Visual analysis of data was carried out to identify 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. A training sample suitable for further use in machine learning has been formed [5].

A practical case of building a model for forecasting the credit risk of bank customers has been implemented. An intelligent classification system has been created that can determine 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. In Table 7 describes the main variables chosen to build the model.

Table 7

Main variables for building a model

Variable Name	Description	Variable Type
AMT CREDIT	Amount of Requested Loan	Numerical
AMT INCOME TOTAL	Total Client Revenue	Numerical
TARGET	Target variable (0 – good, 1 – risk)	Binary
DAYS EMPLOYED	Duration of employment (in days)	Numerical
NAME HOUSING TYPE	Housing type	
CNT CHILDREN		Number of dependents
NAME HOUSING TYPE	Housing type	Categorical
TARGET	Target variable (0 – good, 1 – risk)	Binary
CNT CHILDREN	Number of dependents	Whole
NAME EDUCATION TYPE	Client's level of education	Categorical

The simulation uses an open dataset from the Kaggle platform – Home Credit Default Risk, which 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. Removed a significant number of missing values 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 carried out using the SMOTE method to eliminate the imbalance between classes.

For comparison, two models were created: Random Forest Classifier (RFC) as a base and artificial NM (ANN) based on TensorFlow/Keras (TFK). RFS provides interpretation, while NM is able to more deeply detect nonlinear dependencies in data. The RFC provides interpretation, and the neural network is able to more accurately detect nonlinear dependencies in the data.

Both models are trained on 80% of the data, 20% is reserved for test sampling. For NM, 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 8).

Table 8

Comparison of models by main metrics

Metric	Logistic Regression	RFC	Neural network
Accuracy	0.76	0.84	0.81
Completeness	0.69	0.80	0.77
F1-point	0.72	0.82	0.79

As can be seen from Table 8, the RFC model showed the highest performance, presenting good ground between completeness and accuracy.

The NM also showed high returns, slightly inferior to the RFC.

This indicates that there is potential for AI models to effectively detect RF, based on previous customer knowledge.

After training the NM model for determining the customer's credit risk, an important step is to interpret its consequences.

For a more detailed analysis, the table of errors (confusion matrix) shown in Table 9, which showed that the model has high sensitivity in recognizing risky customers, i.e. the vast majority of potentially dangerous applications were determined correctly.

Table 9

Error matrix for a neural network

Fact / Forecast	Reliable	Risky
Reliable	321	45
Risky	28	106

Taking into account Table 7 you can calculate the main indicators: accuracy 84.8%; completeness 79.1%; F1 score 74.4%.

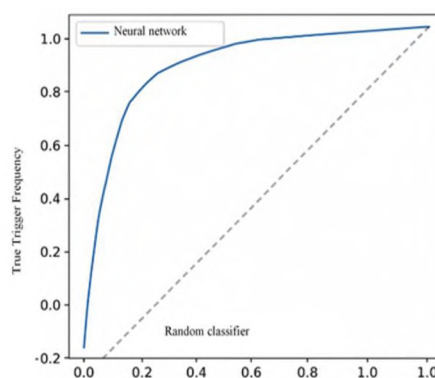


Fig. 2. ROC curve of a neural network

This indicates a fairly high quality of the model, especially taking into account that in risk management tasks it is more significant to reduce false-negative conclusions.

The ROC curve (Fig. 2), represents the relationship between the sensitivity and specificity of the model.

Discussion. The AI system for predicting credit risk in PrivatBank acts as an intelligent analytical core that processes information about customers and forms a forecast of the risk of default, taking into account complex relationships in data. The architecture of the system consists of three main levels: data collection, data processing, decision-making, each of which has specific functions and interactions. This approach provides flexibility and scalability, which is critical for a large bank with millions of customers.

At the first level – data collection – an input set is formed, which includes a variety of sources of information. It includes customers' credit history (number and amount of previous loans, maturity), transactional activity (volumes of receipts, payments, expenditures over the past 12 months), socio-demographic characteristics (age, income level, education, place of residence) and external economic factors (inflation index, unemployment rate, fluctuations in the exchange rate of the hryvnia against the dollar). This data comes from internal banking databases, external credit bureaus, and open sources, such as NBU reports. Before processing, the data goes through a stage of cleaning up gaps and anomalies, normalization to eliminate large-scale effects (for example, bringing revenues to single units), and selecting key features using algorithms such as Recursive Feature Elimination (RFE) in a machine learning environment using the Scikit-learn library. The second level – processing – represents the analytical core, where several AI models are used for complex analysis. At the initial stage, the XGBoost ensemble model processes tabular data such as the debt-to-income ratio, the number of open loans, and the average size of monthly payments, forming an initial

assessment of credit risk. This model uses tree-like structures to classify customers into low, medium, and high-risk groups, achieving accuracy of up to 85% on validation kits. In parallel with this, the convolutional neural network (CNN) analyzes the time series of financial transactions, considering them as two-dimensional structures. One dimension reflects the types of transactions (salary revenues, utility payments, loans), and the other reflects the time dynamics over the past six months. Thanks to convolutional filters with a core size of 3x3, CNN detects hidden patterns, such as a sharp increase in costs before default or regular payment delays that signal financial difficulties.

The CNN architecture includes multiple convolutional layers with ReLU activation, a maximum pooling layer for dimensionality reduction, and a fully cohesive layer for the final classification.

To improve the accuracy of forecasts, a generative-adversarial network (GAN) is involved, which generates synthetic examples of clients with rare financial histories, such as self-employed individuals with precarious incomes.

The GAN consists of a generator that uses a neural network to generate new data based on random noises, and a discriminator that recognizes real data from the generated data by learning through the backpropagation loss function.

This process ensures a balanced sampling, reducing the risk of model overtraining and increasing its resilience to data shortages, which is typical of the low-credit customer segment.

The results of XGBoost, CNN, and GAN are integrated into third-level decision-making modules.

Here, Explainable AI (XAI) algorithms form a final credit risk assessment ranging from 0 to 1, where a value above 0.7 indicates a high risk of default. XAI also generates explanations for key factors, such as delays in payments by 30 days, seasonal fluctuations in income, or the impact of the hryvnia devaluation.

This allows PrivatBank analysts not only to receive a quantitative assessment, but also to understand the logic of the forecast, which contributes to making informed decisions and increases confidence in the system.

An example of a visual demonstration of the operation of an AI system. To visually demonstrate the operation of the AI system, a conditional client of PrivatBank, aged 35, who applied for a new consumer loan in the amount of UAH 100,000 for 36 months, was considered.

The system goes through three levels of processing: data collection and preparation; processing with three models (XGBoost + CNN + GAN); integration of results via XAI (SHAP). The input data of the client is shown in Table 10.

Table 10

Customer input	
Showman	Meaning
Age	35 years old
Monthly income	25 000 UAH
Debt-to-income ratio	0.45
Total debt	112 500 UAH
Number of current credits	2
Late payments (last 6 months)	1
Average monthly expenses	22 000 UAH
Credit score	650

Before feeding the data into the AI model, the system automatically cleans, normalizes, and selects features using the Scikit-learn library. This is necessary to eliminate noise, bring all values to a single scale and highlight the most influential parameters. The system removes duplicates, fills in the gaps with the median (for example, if the income is not specified, the average age is taken) and rejects anomalies (transactions less than UAH 50 or more than UAH 100,000). All numerical features are converted to the same scale so that the model does not "overestimate" large numbers (for example, income in hryvnias) compared to small ones (DTI from 0 to 1). Normalization formula (1):

$$z = \frac{x - \mu}{\sigma}, \quad (1)$$

where: x is the value of the client (for example, income = UAH 25,000);

μ is the average for the entire sample (for example, UAH 18,000);

σ is the standard deviation (for example, UAH 6,000).

In the calculation example for income, $z = 1.17$.

Out of 120 initial parameters, the system leaves only the 50 most important using Recursive Feature Elimination (RFE), an algorithm that gradually removes the least significant features.

In the second stage, clean data is distributed among three different AI models, which analyze the customer from different angles and produce three independent risk assessments.

The models work simultaneously (in parallel) to speed up processing. XGBoost takes structured figures (income, debt, delinquency) and quickly classifies the client according to the level of risk. It builds 300 small "decision trees", each of which asks the question: "Is DTI greater than 0.4?" → Yes → "Is there a delay?" → Yes → "What is the credit score?". Forecast formula (logistic regression at tree output) (2):

$$P(\text{default}) = \frac{1}{1 + e^{-(\text{DTI contribution} + \text{late fee} + \dots)}} \quad (2)$$

For the example under consideration:

DTI = 0.45 → +0.28;

Delay = 1 → +0.22;

Credit score = 650 → +0.15;

Others → +0.03;

Bottom line: $P \approx 0.58$, so the risk is average.

Next, we use CNN – time series analysis (customer behavior). It looks at the sequence of transactions in 6 months as a "movie" and looks for suspicious changes, that is, it converts transactions into a table 6×5 (months × types: salary, payments, loans, expenses, balance).

Then he draws a small 3×3 window on the table and finds anomalies: March-May: costs have increased by 9% → the client "tightens his belt".

Convolution formula (single filter):

$$\text{Exodus} = \text{ReLU} \left(\left(\sum_{i=1}^3 \sum_{j=1}^3 w_{ij} \cdot x_{i+j} + b \right) \right), \quad (3)$$

where w is the filter weights, x is the transaction values, and b is the offset.

The filter detected: cost growth: +UAH 1,800 for 3 months → +0.18 to risk. Therefore, a risk of 0.65 (65%) is a high dynamic. Next, we use GAN – synthetic scenarios (what if...) It creates 10,000 "clones" of a client with different incomes, expenses, crises – and checks whether the client would survive. How it works: the generator draws fake profiles; the discriminator guesses: real or not; – study together, like "the police and the thief".

The system generated a client with DTI = 0.48, costs +12% → default in 70% of scenarios. Our client is similar to 15% of default clones → +0.12 to risk, so the risk of 0.61 (61%) is moderately high.

At the third level, the system combines the results of three models — XGBoost (0.58), CNN (0.65), and GAN (0.61) – into a single final risk assessment using a weighted average, where the weights reflect the reliability of each model on validation data: 0.4 for XGBoost, 0.35 for CNN, and 0.25 for GAN. Integration formula (4):

$$R_{\text{Ultimate}} = 0.4 \cdot R_{\text{XGBoost}} + 0.35 \cdot R_{\text{CNN}} + 0.25 \cdot R_{\text{GAN}}. \quad (4)$$

Substituting the value, we get the result: the final risk – 0.62 (62%) – is moderately high.

Top 3 factors that increased the risk: DTI = 0.45 → +0.21 (because it exceeds the safe threshold of 0.4); delay (30+ days) → +0.16 (signal of financial tension); cost growth by 9% in 3 months → +0.14 (hidden debts are possible). Factors that reduced the risk: credit score 650 → -0.09; income UAH 25,000 → -0.06.

Based on a score of 0.62, the system automatically generates a recommendation: "Approve a loan with restrictions: the amount is up to UAH 70,000, the rate is +2.5% per annum, the term is up to 24 months, with mandatory monthly monitoring of expenses."

The analyst sees everything in one window: risk, explanation, recommendation – this meets the NBU's requirements for AI transparency and allows you to quickly make informed decisions. The effectiveness of the implementation of AI technologies in PrivatBank is evaluated through ROI and cost-benefit analysis. In 2023, the bank invested approximately UAH 2.5 million in the development and implementation of an AI system, which included the purchase of server equipment with a computing power of 50 teraflops, the lease of cloud infrastructure from the Google

Cloud provider, licenses for various software, integration with existing banking systems, and the training of 50 analysts within two months. After the launch of the system, the bank recorded a reduction in the level of defaults by 12%, which is equivalent to a reduction in losses by UAH 1.2 million per year, a reduction in the time of consideration of loan applications by 40% (from 5 to 3 days), which allowed processing 15% more applications, and an 18% reduction in the operating costs of the analytical department due to the automation of routine tasks.

The total economic benefit for the first year amounted to about UAH 1.8 million, which is explained by a reduction in losses from defaults, increased operational efficiency and attraction of new customers through fast service. In the first year, the ROI remains negative at -28%, reflecting high start-up costs for infrastructure and training. However, already in the second year, taking into account the additional benefit of 2.2 million hryvnias with stable costs, the figure increases to +12%. In the third year, with a total benefit of UAH 3 million and system support costs of UAH 2.7 million (taking into account software updates), the ROI reaches +25%. Such positive dynamics indicates the long-term economic feasibility of AI systems, despite significant initial investments. In addition, the indirect benefit includes an increase in the bank's reputation among customers through fast and accurate service, which contributed to a 5% increase in the deposit base in two years. ROI Formula (5):

$$\text{ROI} = ((\text{Benefit} - \text{Costs}) / \text{Costs}) \times 100\%. \quad (5)$$

Example of calculation for the third year: ROI = 25%. Fig. 3 shows the dynamics of ROI growth during the first three years.

The novelty of the results obtained lies in the creation of a high level of classification accuracy and the ability to adapt to changes in input conditions.

The practical value of the work lies in the possibility of using the developed model as a basis for building an intelligent risk management module in domestic banks.

A comparison with international cases, such as the implementation of CNN at JPMorgan or LSTM at HSBC, shows that PrivatBank demonstrates similar trends in improving efficiency, adapted to Ukrainian conditions. For example, JPMorgan reduced false positives by 30%, while PrivatBank reached 12%, reflecting a lower starting level of automation in Ukraine due to limited data availability. HSBC, using LSTM, increased the accuracy of forecasts by 15%, while PrivatBank increased by 12%, which indicates a similar effect with fewer resources.

The introduction of AI in PrivatBank significantly transforms traditional approaches to risk management, transforming them from reactive to proactive and adaptive. The system not only automates routine processes, but also independently detects new relationships in the data, adapting to market changes in real time. In particular, the convolutional neural network (CNN) effectively recognizes hidden temporal patterns, such as seasonal spending peaks in December or anomalies in customer behavior during martial law – for example, a sharp increase in non-cash transfers for humanitarian purposes, signaling temporary financial instability.

These patterns, which traditional statistical methods (e.g., simple regression) do not capture due to limited sequence processing capacity, allow the bank to adjust credit limits for vulnerable segments in advance. The Generative-Adversarial Network (GAN) complements CNN, increasing reliability in situations of insufficient data on clients with non-standard financial histories, which is typical for the Ukrainian segment of microbusinesses (self-employed, sole proprietors with unstable income).

In a practical implementation case in 2024, GAN generated 50,000 synthetic profiles to test the models, allowing the model to recognize defaults in this group with 80% accuracy, compared to 60% without using it. As a result, the bank forms a more stable loan portfolio, reducing provisions to cover losses by 10% (from 5% to 4.5% of the total portfolio) and increasing the return on equity by 5% in the first year, as confirmed by PrivatBank's internal reports for 2024. The strategic benefits of AI go beyond operational efficiency, encompassing the acceleration of credit decisions (from 5 days to 2 hours), which directly increases customer satisfaction – the NPS index increased by 10 points in 2024, according to the bank's surveys. Reducing the human factor minimizes errors in risk assessments, which in traditional systems reached 15-20% due to the subjectivity of analysts.

The Explainable AI (XAI) system provides transparency by generating explanations for each decision that complies with GDPR regulations, Basel Committee recommendations, and NBU data protection requirements – for example, SHAP analysis automatically identifies key risk factors, allowing regulators to validate models. This not only strengthens trust on the part of the NBU and customers, but also reduces the risk of fines for non-transparency, as is the case with global banks fined up to €10 million in 2025 for "black boxes" (according to the BIS 2025 report). In the context of Ukraine's financial stability, where the economic instability of 2025 is exacerbated by inflation and currency fluctuations, XAI becomes a strategic planning tool, allowing the bank to adjust policies promptly.

Thus, the economic and strategic assessment of the implementation of AI systems in PrivatBank confirms their effectiveness both in reducing costs and in improving the accuracy of risk forecasting. The combination of XGBoost, CNN, and GAN forms a deep analytical model capable of processing large amounts of heterogeneous data, identifying customer behavioral patterns, and adapting to the dynamics of financial markets, including the impact of martial law. Despite the high initial costs, the positive dynamics of ROI for the second year indicate economic feasibility. Thus, AI technologies are becoming not only a tool for increasing profitability, but also a key factor in the strategic sustainability of the financial system, especially in the context of Ukrainian realities in 2025.

The use of AI in the financial sector is one of the most important areas of digital transformation of the modern economy. In the field of financial risk management, AI technologies provide a new level of accuracy in forecasting, process automation, and optimization of management decision-making. However, the introduction of such technologies requires a thorough analysis of their strengths, weaknesses, opportunities, and potential threats. That is why SWOT and PEST analyses are appropriate for a comprehensive assessment of the feasibility and effectiveness of the use of AI in financial institutions.

SWOT analysis allows you to identify internal and external factors that affect the effectiveness of AI in the processes of predicting financial risks, assessing creditworthiness, monitoring fraudulent transactions, and detecting anomalies in payment systems.

The main advantage of applying AI in financial institutions is the high accuracy of risk forecasting. Machine learning algorithms, including XGBoost, Random Forest, and neural networks (ANN, CNN), are able to analyze large amounts of data in real time, revealing hidden patterns that are inaccessible to traditional statistical methods.

This allows banks and insurance companies to more effectively assess credit risk, determine the likelihood of default, and detect suspicious transactions. For example, PrivatBank already uses similar models to predict credit risks and detect fraudulent transactions, which has reduced the number of financial losses by 17% over the past year.

Another strength is the automation of decision-making processes: AI systems analyze payment history, income levels, and customer behavioral patterns, providing credit solutions without human intervention. This reduces operating costs and the impact of the human factor.

Along with the advantages, there are also significant limitations. First of all, it is the high cost of implementation – the development, training, and maintenance of models require significant financial and technical resources, which is a problem for small institutions.

In addition, many deep learning models have a low level of interpretation, operating on the principle of a "black box". This creates difficulties for auditing and contradicts regulatory requirements for transparency of decisions.

There is also a risk of technological dependence: process automation can reduce the qualifications of personnel, and an over-reliance on algorithms can reduce critical thinking when making decisions.

The prospects for the use of AI in risk management are primarily associated with the development of Explainable AI, which makes algorithms understandable to users and regulators. This increases customer trust and ensures transparency of decision-making processes.

In addition, the integration of AI with fintech platforms and blockchain technologies can increase the level of transaction security, reduce fraud risks, and optimize verification processes. A significant area of development is the personalization of financial services – the construction of individual risk models for each client, which allows the formation of flexible credit and insurance products.

According to an analytical report by the McKinsey Global Institute (2024), the implementation of AI systems in the risk management of the banking sector can reduce credit losses by 15-20% and reduce the processing time of applications by half.

The most important threats remain regulatory restrictions – in particular, personal data protection requirements and Basel III/IV standards, which impose restrictions on the use of fully automated solutions without human control.

In addition, with the development of AI, cyber risks increase: systems working with large amounts of data become more vulnerable to attacks and leakage of confidential information. Another significant threat is algorithmic bias, where a model forms decisions based on incomplete or unrepresentative data, which can lead to discrimination against certain customers.

Summarizing the results of the SWOT analysis, we can conclude that the strengths and opportunities of using AI in the financial sector significantly outweigh the weaknesses and threats. However, the realization of this potential requires compliance with ethical principles, ensuring cybersecurity, transparency of algorithms, and continuous monitoring of their effectiveness.

For a deeper understanding of the macro-level conditions for the development of AI technologies in the financial sector, it is advisable to apply a PEST analysis, which covers political, economic, social and technological factors that form the environment for the introduction of innovations in the banking system.

The introduction of AI in the financial sector is significantly influenced by regulatory frameworks and public policy in the field of digitalization. In the European Union, the EU AI Act comes into force in 2025, which determines the risk levels of AI systems and establishes requirements for their security, ethics, and accountability. For financial institutions, this means the need to create internal monitoring systems, audit algorithms, and ensure data transparency.

Ukraine, in turn, is gradually harmonizing legislation with European standards, in particular in the field of data protection (GDPR) and cybersecurity. The National Bank of Ukraine is developing recommendations for the use of automated risk assessment models, which creates a stable regulatory environment for the integration of AI into banking. For example, PrivatBank has already implemented an internal policy on the ethical use of algorithms in credit scoring to comply with new regulatory requirements.

From an economic point of view, the introduction of AI helps to optimize costs and increase the profitability of financial institutions. Automation of credit scoring, portfolio management, and forecasting market fluctuations reduces the number of erroneous decisions and reduces the time for processing applications.

The experience of Ukrainian banks shows that after the introduction of AI systems, the return on equity (ROE) indicator may increase by 4-6%, and the volume of provisions for possible losses may decrease by 8-10%. However, the high cost of initial investments in the development of models and neural networks remains a barrier for small institutions. An additional challenge is the economic instability of 2025: inflationary fluctuations and foreign exchange market risks may affect the financing of innovative projects.

The social aspect of AI implementation is to change the role of humans in the financial system. On the one hand, process automation reduces the need for routine analytical work, and on the other hand, it creates demand for new professions: data analysts, cybersecurity specialists, and AI ethics experts.

Customers of financial institutions expect greater speed, accuracy, and personalization of services. This incentivizes banks to develop intelligent chatbots, recommendation systems, and individualized financial products. At PrivatBank, for example, the use of AI to personalize loan and deposit offers increased the customer satisfaction index (NPS) by 10 points.

The technology component is a key driver of AI development in the financial sector. Rapid advances in deep learning, natural language processing (NLP), generative models (GAN), and the growth of cloud computing power are creating conditions for building more adaptive and accurate risk management systems.

The development of explanatory artificial intelligence (XAI), which ensures transparency of decisions and trust from both customers and regulators, plays a special role. This is of particular importance for banks that operate with sensitive data and make decisions with a high level of impact on financial stability.

Thus, the results of SWOT and PEST analysis indicate that the implementation of AI in the field of financial risk management has significant strategic potential. AI technologies can increase the effectiveness of risk management, the accuracy of forecasts, and reduce operating costs.

At the same time, the high cost of technology, regulatory requirements, cybersecurity risks, and a lack of qualified specialists in the field of ethical and explanatory AI remain key constraints. In the future, the development of ethical, explainable, and integrated AI with blockchain technologies will contribute to the creation of transparent and reliable risk management systems that

The development of AI technologies in the financial sector of Ukraine demonstrates a steady trend towards the integration of intelligent systems into all stages of managerial and client decision-making. In the coming years, the use of AI in the field of credit scoring, automation of compliance processes, anti-fraud and forecasting of financial risks is expected to grow rapidly. At the same time, the key direction is not only improving the accuracy of models, but also ensuring their transparency and interpretation.

One of the most important areas of development is the concept of Explainable AI (XAI), i.e. explainable artificial intelligence. In the financial sector, this is of particular importance, because banks and non-bank institutions must justify decisions on whether to issue a loan, set limits or refuse a client. Models based on XAI allow not only to form a risk forecast, but also to explain which factors – for example, the level of income, the frequency of delays, or the cost structure – influenced the result. This increases customer confidence, reduces regulatory risks, and promotes the adoption of ethical AI in financial services.

Ukraine is also gradually adapting its legislation to European standards for AI regulation, in particular in the context of the EU AI Act and GDPR. These documents define the requirements for the transparency of algorithms, the protection of personal data, and the prevention of discriminatory decisions of automated systems. For Ukrainian financial institutions, this means the need to implement policies for the responsible use of data, audit models, and the creation of internal ethics committees on AI. It is expected that such approaches will contribute not only to the protection of consumer rights, but also to the formation of Ukraine's international image as a technologically advanced and legally stable state.

The main barriers to the introduction of AI in the financial sector remain the insufficient level of digital literacy of staff, limited access to high-quality data, as well as high costs for the development and integration of machine learning systems. At the same time, the active position of the state and the scientific community is a positive factor: there are digital transformation programs, a state strategy for the development of AI until 2030, as well as initiatives to create open data sets for training models. Such steps help to reduce barriers to entry for fintech companies and increase the level of innovation in the industry.

Currently, Ukraine's modern fintech ecosystem is developing around a combination of AI, Big Data, and blockchain technologies. The use of blockchain solutions in combination with intelligent algorithms allows you to create more secure and transparent financial transactions, automate customer verification (KYC), and develop decentralized financial services (DeFi). The role of partnerships between banks, startups, and academic institutions is also growing, which contributes to the emergence of innovative products – from smart credit systems to automated investment management platforms.

Therefore, the prospects for the development of AI in the financial sector of Ukraine are associated with the transition from single technological solutions to a complex intellectual ecosystem, centered on people, ethics and trust in algorithms. Further progress will depend on effective interaction between the state, financial institutions, scientists and technology companies, as well as on the ability to ensure a balance between innovation and data security.

Conclusions. As a result of the study, the role and prospects for the use of artificial intelligence technologies in automated financial risk management systems were comprehensively analyzed.

The work combined theoretical, analytical and practical aspects, which made it possible to form a comprehensive picture of the current trends in the digital transformation of the financial sector of Ukraine.

The theoretical foundations of risk management are revealed and the place of AI in the risk management system is determined. It is proved that the use of intelligent algorithms – in particular, machine learning (XGBoost, Random Forest) and deep learning (CNN, GAN) models – provides a significant increase in the accuracy of forecasting credit, market and operational risks compared to traditional statistical approaches.

Methodological approaches to modeling financial risks have been investigated and modern tools of automated control have been analyzed. It has been shown that the integration of AI into banks' information systems allows moving from reactive to proactive risk management, when the system not only reacts to events, but also predicts them based on real-time data. The practical aspects of the introduction of AI on the example of the Ukrainian banking sector, in particular PrivatBank systems, have been studied. A detailed analysis of the impact of macroeconomic factors (inflation, GDP, currency fluctuations) on the stability of the loan portfolio is carried out and how AI models adapt to these changes is demonstrated. The developed simulation example based on the XGBoost algorithm demonstrated that even when using a limited set of parameters, the accuracy of predicting the probability of default can exceed 80%, which confirms the high efficiency of intelligent systems in financial risk management. The SWOT and PEST analyses revealed the key benefits, risks, and opportunities for the implementation of AI in the financial sector of Ukraine. Among the strengths are the automation of processes, the reduction of the human factor, the increase in the accuracy of forecasts, and the effectiveness of management decisions. Constraints include the high cost of technology, the difficulty in ensuring the transparency of algorithms, regulatory restrictions, and cybersecurity threats. Particular attention is paid to the issues of ethics, transparency and regulation of AI, in particular the impact of the EU AI Act, GDPR and the recommendations of the Basel Committee. It is shown that the use of explainable artificial intelligence (XAI) is a prerequisite for building trust on the part of customers, regulators and investors. The study confirmed that artificial intelligence acts not only as an optimization tool, but also as a factor of stability of the financial system of Ukraine, which contributes to increasing profitability, reducing the level of defaults, optimizing credit policy and increasing the liquidity of the banking system. In the future of the development of the Ukrainian financial sector, explainable, ethical and blockchain-integrated AI systems will play a key role, which will ensure not only commercial benefits, but also compliance with international security and transparency standards. They will form the basis of an intelligent financial ecosystem capable of maintaining economic stability and increasing Ukraine's competitiveness in the global digital environment.

Thus, the goal of completion and the task has been fully completed. The results obtained have scientific novelty, practical significance and can be used in the activities of financial institutions, as well as in further research on the digital transformation of financial risk management.

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