DOI: 10.55643/fcaptp.5.70.2026.5313

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Received: 26/08/2026
Accepted: 22/10/2026
Published: 31/10/2026

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THE ARTIFICIAL INTELLIGENCE REVOLUTION IN FINANCE: FROM ALGORITHMS TO STRATEGIC SOLUTIONS

ABSTRACT

A rapid development of artificial intelligence (AI) technologies is transforming the financial sector, changing approaches to automating operations, analyzing data bulk, forecasting, risk management, customer service, and making management decisions. The relevance of the study is due to the need to transition from the fragmented and predominantly operational use of algorithmic tools to their systemic integration into strategic management in finance. The purpose of the study is to systematize the areas of application of AI in the financial sector and substantiate the conceptual model of the transition from the operational use of algorithmic tools to the strategic level of management. To achieve the set goal, systemic, historical-logical, comparative, and classification methods were used. The main results of the study are the identification of four stages of the evolution of AI applications in finance: algorithmic-rule, machine learning, deep learning, and generative-strategic. The key areas of AI use are systematized by the level of managerial influence - from the automation of routine operations and support of individual business processes to forecasting, risk management, personalization of financial services, and the formation of strategic management decisions. The technological, regulatory, reputational, ethical, and systemic risks associated with scaling AI in the financial sector are summarized. A five-level maturity model of AI application is proposed, which involves a sequential transition from experimental, operational, and integrated levels to the level of managerial transformation and strategic use of technologies.

It is concluded that the strategic value of AI is determined not by the number of implemented technological solutions, but by the degree of their integration into the corporate governance system, the quality and availability of data, the effectiveness of model management, personnel competencies, the explainability of algorithmic solutions, compliance with regulatory requirements, and the effectiveness of risk control. The strategic integration of AI creates the prerequisites for increasing the adaptability, competitiveness, and sustainability of the financial sector.

Keywords: artificial intelligence, financial technology, algorithmic trading, machine learning, explainable artificial intelligence, risk management, strategic management, fintech

JEL Classification: G10, G20, G32, C45, C55, O33

INTRODUCTION

The financial sector has traditionally been one of the first recipients of technological innovations, as its activities are largely based on processing large amounts of quantitative information, forecasting, and risk management under the conditions of uncertainty. While the initial stages of digitalization were mainly about automating standard operations, over the last decade there has been a qualitative transition from the use of statistical models to the implementation of artificial intelligence (AI) systems capable of self-learning, identifying complex nonlinear dependencies, and generating recommendations for making management decisions.

This issue became particularly relevant in 2023-2026 due to the massive spread of generative artificial intelligence models, which went beyond purely analytical tasks and began to be used to support strategic planning, scenario analysis, communication with investors, and the formation of management reporting. According to industry research, the share of financial institutions that have implemented some kind of AI-based solution exceeds ninety percent, and the volume of the relevant market segment is projected to grow at an outpacing rate over the next decade. This indicates that artificial intelligence has ceased to be a purely technological tool for analytics and risk management departments and is gradually becoming an element of corporate strategy. At the same time, the rapid introduction of AI into financial activities is accompanied by a number of conceptual and practical problems. First, most high-performance machine learning models are "black boxes," making it difficult to justify decisions based on them to regulators, customers, and boards of directors (Wilson, 2025). Secondly, the regulatory environment is not keeping up with the pace of technological development, as a result of which the financial sector is forced to operate in conditions of increased legal uncertainty. Third, the question of under what organizational conditions algorithmic tools truly become a factor of strategic advantage, rather than remaining isolated point solutions of individual departments, remains insufficiently investigated. These circumstances necessitate a comprehensive scientific understanding of the evolution of the application of artificial intelligence in the financial sector - from highly specialized algorithms to tools to support strategic decisions, as well as the systematization of the associated opportunities and risks.

For the financial system of Ukraine, the issue of implementing artificial intelligence has an additional dimension of relevance. On the one hand, limited resources for independent development of complex models encourage the financial sector to use ready-made platform solutions and AI cloud services, which raises the question of adapting such solutions to the peculiarities of the national regulatory environment and the specifics of the local market. On the other hand, increased integration with the European financial space requires harmonization of approaches to managing the risks of AI applications with relevant European Union initiatives on regulating artificial intelligence in the financial sector (Regulation, 2024). At the same time, martial law and the associated challenges to financial stability increase the importance of artificial intelligence technologies as a tool for the rapid detection of fraud, cyber threats, and the financing of illegal activities, as well as a means of supporting decision-making in conditions of increased uncertainty and limited human resources in the financial market. In such conditions, the question of under what organizational prerequisites algorithmic tools are able to move from point operational applications to full support of strategic management decisions acquires not only theoretical, but also applied significance.

LITERATURE REVIEW

The speedy progress of artificial intelligence in recent years is shaping a new paradigm for the functioning of the financial sector, changing not only information processing technologies, but also approaches to forecasting, risk management, investment analysis, and strategic financial decision-making. While in the initial stages of digital transformation, AI was mainly used to automate individual operations and build predictive models, the current stage is characterized by the transition to generative artificial intelligence (Generative AI), large language models (Large Language Models, LLMs), and AI agents capable of performing complex sequences of analytical and management actions (Aldasoro, 2024). This evolution indicates the formation of a new stage of digital transformation of the financial sector, within which AI is no longer considered only as a tool for automating individual operations, but as a component of the management decision-making system (Goodell,2021; Nazareth, 2023; Onyshchenko, 2026).

One of the fundamental studies on the digital transformation of the financial sector is the work by J. W. Goodell, S. Kumar, W. M. Lim & D. Pattnaik, who, in terms of bibliometric analysis, systematized research on AI and machine learning in finance and identified the main thematic clusters of scientific literature (Goodell, 2021). L. Cao proposed a comprehensive classification of AI methods in the financial industry, highlighting key application areas: market forecasting, portfolio management, credit scoring, fraud detection, and algorithmic trading (Cao, 2022). The digitalization of the economy has contributed to the growing role of AI in predicting bankruptcies, stock prices, agricultural prices, anti-money laundering, and big data analysis (Ahmed, 2022). However, most current research focuses on machine learning, risk management, financial markets, banking, and decision-making automation (Bahoo, 2024). Thus, the first stage of the modern AI revolution in finance is associated with the spread of machine and deep learning (Aldasoro, 2024). Algorithmic approaches are particularly actively used in credit scoring, bankruptcy prediction, liquidity assessment, fraud detection, portfolio management, and financial market forecasting. N. Nazareth & Y. V. R. Reddy note that machine learning and deep learning are used in six key financial areas: stock markets, portfolio management, cryptocurrencies, foreign exchange markets, financial crises, and bankruptcies (Nazareth, 2023). S. Shi emphasized the ability of machine learning to work with nonlinear relationships and large data sets in the field of credit risk (Shi, 2022).

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A. Robisco & J. M. Carbó empirically demonstrated that ML models can provide higher accuracy in predicting credit default compared to traditional models and potentially reduce banks' need for regulatory capital (Alonso-Robisco, 2022). The development of algorithmic approaches also extends to systemic risks. R. Liu and C. S. Pun proposed the use of machine learning to improve the measurement of systemic risk, allowing the integration of a broader set of macroeconomic variables and overcoming the limitations of traditional econometric models (Liu, 2022). At the same time, there is a paradox of AI transformation: AI can simultaneously increase the efficiency of the financial system and create new systemic risks due to procyclicality, technology concentration, model interdependence, and unknown risks (Daníelsson, 2022). Thus, the research on machine learning in liquidity risk modeling demonstrates the potential of algorithmic models for improving banking supervision and assessing the ability of financial institutions to meet short- and long-term obligations.

Currently, transparency, explainability, fairness, and accountability are of fundamental importance for credit, investment, insurance, and regulatory decisions. Explainable AI (XAI) is becoming a critical condition for using complex models in financial decisions (Černevičienė, 2024), and technological solutions must be combined with the requirements of financial management, information systems, and corporate governance (Weber, 2024). The use of XAI to combat financial fraud is of particular importance. Thus, the authors demonstrated the possibility of combining high forecasting accuracy with explanations based on Shapley values, focusing on the needs of users of financial information (Zhou, 2023). Current research shows that AI models can improve the accuracy of credit scoring, but at the same time can reproduce biases embedded in the training data. Therefore, the development of responsible credit scoring involves a combination of ML, knowledge acquisition, and fairness control procedures.

A fundamentally new stage of the AI revolution occurred after the spread of generative AI and large language models (LLMs). Unlike classic machine learning, which mainly predicts a certain outcome, generative models are able to work with unstructured information, form analytical conclusions, generate text, interpret financial documents, and interact with the user in natural language. Large language models open up new possibilities for financial analysis, forecasting, information management, and decision support (Li, 2023). Generative models can be useful for generating research ideas, information retrieval, and preliminary analysis, but the quality of the results depends largely on the user's expert knowledge and the quality of the input data (Dowling, 2023). J. H. Kim considers the possibility of using ChatGPT as a kind of "quantum" that helps shape decisions about the choice of asset classes depending on economic conditions (Kim, 2023). Comparing ChatGPT to roboadvisors also demonstrates the promise of generative models for personalized investment recommendations. At the same time, the quality of such recommendations depends on the structure of the request, the investor profile, and the limitations of the model itself. There is also significant potential for ChatGPT for sentiment analysis in the foreign exchange market, particularly compared to FinBERT (Fatouros, 2023).

The Ukrainian scientific discourse on the application of artificial intelligence in the financial sector is characterized by a gradual transition from researching the general possibilities of digitalization to assessing the specific financial effects and risks of using intelligent technologies. Thus, I. Zhuravliova studied the application of AI in the financial sector through a system of indicators of technological maturity and efficiency, which allows moving from assessing the fact of digitalization itself to determining its impact on the quality of financial decisions, risk management, and financial stability (Zhuravliova, 2026). C. Savchenko researched the transformation of the financial market under the influence of digital innovations, considering artificial intelligence as one of the key technological drivers of the development of modern financial services. The author focuses on the combination of artificial intelligence, Big Data, blockchain, FinTech, and algorithmic marketing technologies that are changing the approaches of financial institutions to communications automation. This approach gives grounds to consider AI not only as a tool for automating individual operations, but as a component of a comprehensive transformation of business models in the financial market (Savchenko, 2025).

A separate area of research is the use of AI in banking and financial risk management. O. Onyshchenko, V. Ternovska, and V. Kovaliov studied the integration of AI into the activities of financial and credit institutions, focusing on the transformation of accounting and analytical systems, automation of financial processes, risk management, and the impact of intelligent technologies on financial stability and the quality of management decisions (Onishchenko, 2026). The authors attach particular importance to generative and agent AI (Onyshchenko, 2025). A. Chornovol and co-authors analyzed the use of AI in financial risk management of banks and insurance companies, focusing on the technology capabilities to improve risk identification, assessment, and monitoring procedures (Chornovol, 2024). M. Ganciak explores a new stage in the development of financial technologies – the use of AI agents in the financial market, linking their prospects with the transformation of banking, payment, and investment services in Ukraine (Ganciak, 2026). D. Kretov and T. Korolyova analyze the impact of AI on the competitive environment of banks, emphasizing its use in customer interaction, risk management, analytics, monitoring, and execution of financial transactions (Kretov, 2026).

C. Smerichevsky and M. Bilychenko are developing the direction of using Explainable AI for analyzing the financial security of enterprises, in particular predicting bankruptcy and supporting anti-crisis management (Smerichevsky, 2026). This approach is important for the financial sector, as it combines the predictive capabilities of AI with the requirements for the interpretability of algorithmic solutions (Smerichevsky, 2026). M. Bilichenko also investigates the assessment of the financial security of an enterprise using machine learning methods, which indicates the formation in Ukraine of a separate research direction at the intersection of artificial intelligence, financial analysis, and economic security (Bilichenko, 2024). The use of machine learning in this context expands the capabilities of traditional financial analysis by identifying complex relationships between financial indicators and business risks. V. Rozdobudko and A. Myronov are investigating the use of AI to analyze enterprise profits, linking its application to improving financial management and increasing the financial stability of business entities (Rozdobudko, 2025).

Therefore, AI is increasingly being studied as a tool capable of influencing financial strategy formation, capital allocation, risk management, investment policy, and the competitiveness of the financial sector.

AIMS AND OBJECTIVES

The purpose of the article is to systematize the areas of application of artificial intelligence in the financial sector and to substantiate the conceptual model of the transition from the operational use of algorithmic tools to their application at the level of strategic management in finance.

To achieve the purpose, the following research tasks were identified:

1. To trace the evolution of the application of artificial intelligence technologies in finance and identify its main stages.
2. To systematize key areas of practical application of AI in financial activities and compare them with the level of managerial influence.
3. To summarize the main risks and limitations associated with the implementation of AI in finance.
4. To develop a conceptual model of maturity levels for the application of AI in the financial sector.

METHODS

The research is based on the application of general scientific methods of cognition. The system analysis method was used to study artificial intelligence in the financial sector as a holistic set of technologies, organizational practices, and regulatory mechanisms that are in constant interaction. The historical-logical method was used to identify the stages of evolution of the application of AI in finance - from early statistical models and algorithmic trading to modern generative systems for supporting strategic decisions. Comparison of areas of application of artificial intelligence (credit scoring, fraud detection, algorithmic trading, portfolio management, customer service, strategic forecasting) according to the criteria of the level of automation, the degree of human participation in decision-making, and the level of managerial influence - operational, tactical, or strategic - was carried out using comparative analysis. The classification method allowed us to systematize the risks of implementing AI in finance - technological, regulatory, reputational, and ethical.

The information base for the study was scientific publications dedicated to the application of artificial intelligence and machine learning in the financial sector, in particular, systematic reviews and bibliometric studies, as well as analytical reports from international organizations and consulting companies on the status of AI implementation in the financial industry. The time frame of the study is determined by the period of the most active development of applied machine learning technologies in finance – from the spread of deep learning methods to the mass implementation of generative AI. The use of these methods in combination made it possible to build an author's conceptual model that summarizes the logic of the transition from the algorithmic to the strategic level of application of artificial intelligence in a financial institution.

RESULTS

Generalization of the results of modern research on the use of AI in finance made it possible to establish that the evolution of artificial intelligence in the financial sector is characterized by the transition from the use of algorithms to perform individual standardized operations to the integration of intelligent systems into the processes of forecasting, risk management, and strategic decision support, and has four main stages of evolution: algorithmic-rule, machine learning, deep

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learning, and generative-strategic. The first stage (approximately until the mid-2000s) was characterized by the use of formalized rules, statistical models, and algorithms to automate individual repetitive operations. At this stage, the digitalization of finance was mainly aimed at increasing the speed of information processing, automating calculations, initial risk assessment, and supporting operational activities. Accordingly, the managerial impact of such technologies was mainly operational, as the algorithm performed a predetermined procedure, while the final decision remained with the employee (Aldasoro, 2024). The role of humans in decision-making at this stage remained decisive, and algorithms performed an auxiliary analytical function.

The second stage (late 2000s - mid-2010s) is associated with the spread of algorithmic and high-frequency trading, as well as the application of support vector methods, ensemble methods, and early neural networks for forecasting financial time series. At this stage, there is a transition from rigidly defined rules to models capable of independently detecting patterns in large data sets. Some of the most prominent areas have been credit scoring, fraud detection, risk assessment, algorithmic trading, and customer interaction automation (Bahoo,2024). In 2017, the Financial Stability Board documented the use of AI/ML for credit quality assessment, insurance pricing, capital optimization, trading position analysis, trading signal detection, compliance, supervision, data quality assessment, and fraud detection. Thus, in the second stage, AI gradually evolved from a tool for automating operations into a tactical management instrument, as the results of algorithmic analysis increasingly began to inform managerial decision-making.

In the third stage (mid-2010s - early 2020s), deep learning and scaling of data-driven models are being implemented, and neural networks, large arrays of structured and unstructured data, more complex predictive models, and high-performance computing are being actively used. During this period, AI capabilities are expanding in forecasting market indicators, portfolio management, credit risk assessment, fraud prevention, personalization of financial products, and analysis of customer behavior. As a result, there is a shift in managerial influence from a single transaction to tactical management of financial processes (Aldasoro, 2024). It is at this stage that the problem of the "black box" of algorithmic models becomes particularly acute due to increased regulatory requirements for transparency and accountability of automated decisions, particularly in the area of lending to individuals and legal entities.

The fourth, modern stage (since the early 2020s) was formed as a result of the spread of generative AI, large language models, and intelligent agents. Unlike previous generations, such systems are able to work with unstructured information, generate and summarize texts, search for information, and support the preparation of analytical materials and program code. The Financial Stability Board notes that the emergence of generative AI and large language models has significantly expanded the range of its possible applications in the financial sector (FSB, 2026). Bank for International Settlements defines modern transformation as a sequential shift from rule-based systems to machine learning and generative AI, spanning financial intermediation, insurance, asset management, and payments (Aldasoro, 2024). At the same time, each subsequent generation of AI increases the financial system's capabilities for information processing, pattern recognition, and forecasting, while simultaneously creating new risks associated with data privacy, algorithmic discrimination, market concentration, and the interconnectedness of financial institutions (Aldasoro, 2024).

Therefore, it is appropriate to present the evolution of the application of AI in finance as a logical chain (Figure 1), in which each subsequent stage is based on the technological and organizational achievements of the previous one and is characterized by the expansion of functional capabilities, the level of autonomy, and the strategic influence of artificial intelligence on financial decision-making processes.

The evolution of AI in finance presented in Figure 1 reflects not only a consistent change in technological approaches, but also a gradual expansion of the areas of its practical use and an increase in the level of influence on management processes. While in the early stages, AI mainly performed the functions of automation and support of operational procedures, the modern stage is characterized by its involvement in analytical, predictive, and strategic financial decisions.

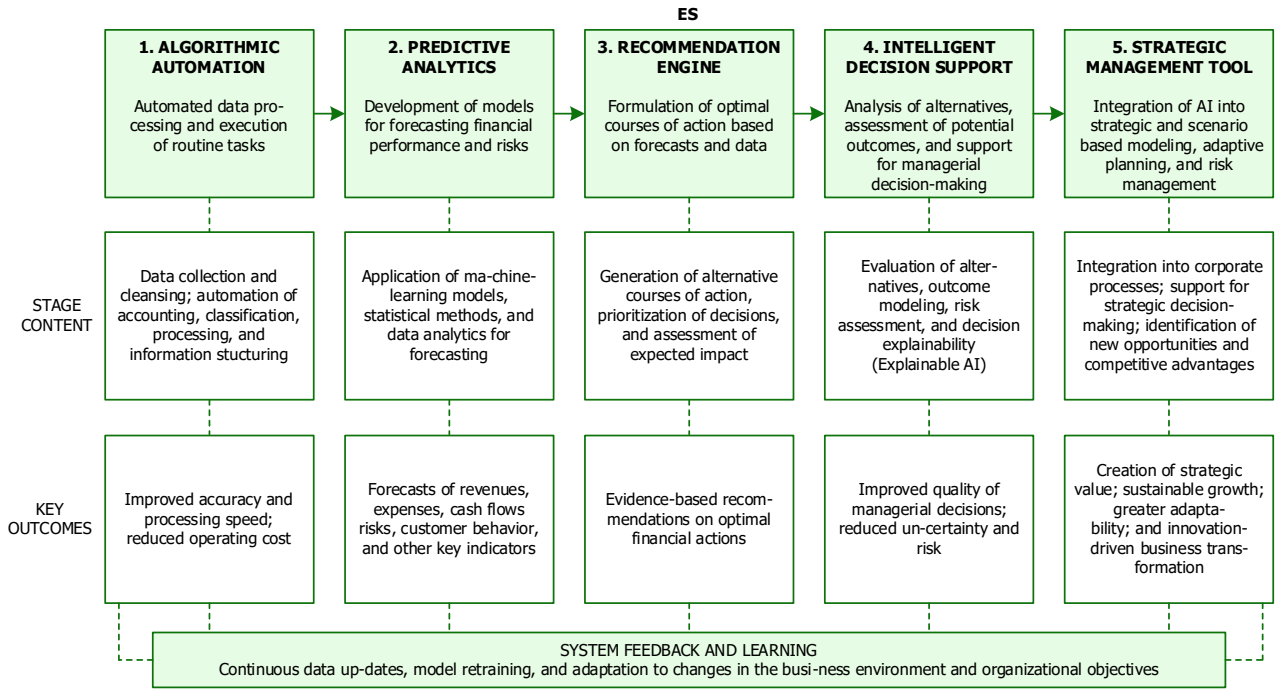


Figure 1. Algorithm of AI evolution in finance.

In view of this, it is advisable to systematize the main areas of application of AI in financial activities and determine the appropriate level of their managerial influence (Table 1).

Table 1. Main areas of application of AI in finance and level of managerial influence. *(Source: developed by the author based on FSB, 2017; FSB, 2024; FSB, 2026; Aldasoro et al., 2024)*

Direction of application	Basic technologies	Automation level	Human participation	Level of managerial influence	Key risk
Fraud detection	ML, anomaly detection, neural networks	High	Low/ average	Operational	False positive solutions, adaptation of fraudulent schemes
AML/KYC and compliance	ML, NLP, GenAI	High	Average	Operational	Classification errors, regulatory risks
Credit scoring	ML, predictive analytics	High	Average	Tactical	Discrimination, model opacity
Personalization of financial products	ML, recommendation systems	Average / high	Average	Tactical	Confidentiality, manipulative pricing
Algorithmic trading	ML, deep learning, reinforcement learning	Very high	Low	Tactical / strategic	Procyclicality, model and market risk
Portfolio management	ML, predictive analytics, optimisation	Average / high	High	Tactical	Forecasting errors, model concentration
Risk management	ML, stress testing, predictive analytics	Average	High	Tactical / strategic	Model risk, data drift
Customer service	NLP, LLM, GenAI, chatbots	High	Low/medium	Operational / tactical	Hallucinations, incorrect recommendations
Document analysis and information search	NLP, LLM, GenAI	High	Average	Operational / tactical	Generation errors, data leaks
Strategic forecasting	ML, deep learning, GenAI, scenario analysis	Average	High	Strategic	Forecast uncertainty
Support for strategic decisions	GenAI, predictive analytics, AI agents	Average	Very high	Strategic	Overreliance on AI, errors, and poor explainability

Thus, in the field of credit scoring, artificial intelligence makes it possible to take into account a much wider range of variables compared to traditional scoring models, including behavioral and alternative data, which increases the accuracy of assessing the creditworthiness of borrowers. At the same time, it is in this area that the requirement for explainability

DOI: 10.55643/fcaptp.5.70.2026.5313

of the decision is particularly acute, since the refusal to provide credit must be justified to the client and the regulator, which necessitates the active use of XAI methods, in particular approaches based on Shapley values, to reconcile the accuracy of the model with the possibility of its interpretation. In the area of fraud detection, machine learning algorithms, including anomaly detection methods and ensemble classifiers, make it possible to analyze transactions in real time and detect atypical patterns of behavior that are difficult to capture using hard-coded rules. The key operational challenge here remains balancing the model's sensitivity (ability to detect real fraud) with the level of false positives that create additional burden on customers and security departments. In algorithmic and high-frequency trading, artificial intelligence performs not only an analytical but also an executive function, independently forming and implementing trading decisions based on predictive time series models and reinforcement learning methods. This provides a significant increase in the speed of reaction to market changes, but at the same time creates systemic risks associated with the possibility of synchronous actions of many algorithmic systems in response to the same type of market signals. The use of AI in portfolio management makes it possible to improve traditional approaches to optimizing the ratio of return and risk by taking into account nonlinear dependencies between assets and dynamically adjusting the portfolio structure. The main limitation of this direction is the risk of model overtraining on historical data, which can lead to low predictive quality under conditions of structural changes in the market.

In the field of customer service, natural language processing and generative AI technologies make it possible to automate a significant portion of customer communication – from responses to typical requests to personalized financial advice. This increases operational efficiency, but creates reputational risks in the event of incorrect or misleading responses from automated systems, which necessitates a clear distinction between areas where decisions can be made automatically and areas that require mandatory human confirmation. Finally, the direction of strategic forecasting and scenario analysis, which relies on generative artificial intelligence and large language models, is at the earliest stage of development among the considered directions. Its potential lies in the ability to quickly generate and compare alternative market development scenarios, automatically analyze regulatory changes, and prepare initial versions of strategic documents, while the main limitation remains the need to ensure transparency and verifiability of such recommendations for senior management.

As shown in Table 1, most existing applications of artificial intelligence are still focused on the operational and tactical levels of management - automating individual processes and supporting medium-term decisions of departments. At the same time, areas related to strategic forecasting, scenario analysis, and decision support at the senior management level are at the initial stage of development. Therefore, the technological complexity of AI is not identical to the level of its managerial influence, and the criterion for transitioning to a higher level of maturity should be considered not the number or complexity of AI models used, but the degree of their integration into the financial system.

Thus, the operational level involves the use of AI to automate individual, mostly routine processes – document processing, initial scoring, chatbots for customer service. Decisions at this level are local in nature, are made within a separate unit, and, as a rule, do not require significant changes in the organizational structure of the institution. The tactical level is characterized by the integration of AI models into risk management, pricing, and customer analytics processes at the level of functional units – risk management department, treasury, compliance department. At this level, there is a need to develop internal policies regarding model validation, monitoring their quality, and explainability of decisions made. The strategic level involves the use of artificial intelligence as a decision support tool at the level of senior management and the board of directors - for scenario analysis, evaluation of strategic alternatives, forecasting macrofinancial risks, and shaping a long-term competitive position of an institution. The transition to this level requires not only technological readiness, but also changes in organizational culture, including building management trust in algorithmic recommendations, developing internal expertise in explainable AI, and integrating relevant issues into the corporate governance system (FSB, 2026).

In general, as the comparison of data in Table 1 shows, the areas of AI application differ significantly not only in terms of leading technologies, but also in terms of the ratio of benefits and risks: operational-level areas are usually characterized by more mature technological solutions and established risk management practices, while tactical and, especially, strategic-level areas are characterized by a higher potential for creating added value for the institution, but also by higher uncertainty regarding the quality and reliability of the recommendations received.

At the same time, the expansion of the role of artificial intelligence from algorithmic automation to a strategic tool is accompanied by an increase in the complexity of the risks associated with it. While in the initial stages the focus is mainly on the accuracy of algorithms and data quality, as AI is integrated into management and strategic decision-making processes, additional technological, regulatory, reputational and ethical challenges arise (Table 2).

Table 2. Classification of risks of AI application in the financial sector. *(Source: systematized by the author based on Financial Stability Board (2017, 2024); Crisanto (2026); Aldasoro (2024); European Parliament & Council of the European Union (2024).*

Risk group	Main manifestations of risks	Key implications
Technological	Low data quality; model errors; cyber threats; insufficient infrastructure reliability; dependence on external technology providers; difficulty integrating AI solutions with legacy systems; insufficient interpretability and auditability of models	Prediction and decision-making errors; reduced reliability of AI solutions; operational and cyber risks
Data and Model	Insufficient data quality, completeness and representativeness; privacy issues; data security and access; data bias; insufficient data control at the stages of training, testing and improving models	Incorrect model results; algorithmic bias; AI scaling limitations
Regulatory	Non-compliance with data protection requirements; non-discrimination; consumer protection; cybersecurity; model risk; liability for decisions; EU AI Act requirements	Fines and sanctions; legal liability; restrictions on the use of AI solutions; regulatory losses
Regulatory and Legal	AI errors in lending, advice, investment recommendations and compliance; generating convincing but incorrect information; opacity of decisions	Loss of customer trust; reputational damage; customer churn; financial losses
Ethical and social	Algorithmic discrimination; data bias; opacity of automated decisions; overuse of personal information; lack of human control	Violation of customer rights; unequal treatment; decline in social trust in AI
Systemic	Concentration of technology providers; interdependence of financial institutions; cyber risks; model risk; spread of similar algorithmic strategies	Scaling failures across institutions; increasing interconnectedness; threats to financial stability

Thus, the risks of AI are not solely a technical problem. They cover all levels, from data quality and algorithm correctness to management accountability and financial stability.

The identified risks indicate that the effectiveness of the application of artificial intelligence in the financial sector is determined not only by the availability of appropriate technological solutions, but also by the level of organizational, managerial, and regulatory readiness of the financial institution to use them. Accordingly, the same AI technologies can create fundamentally different economic and managerial effects depending on how well they are integrated into business processes and the decision-making system. This necessitates a transition from analyzing individual areas and risks of AI application to assessing the level of maturity of the financial sector in using relevant technologies.

In this context, it is appropriate to consider the maturity of AI application as a comprehensive characteristic that reflects the degree of technological readiness, the quality of data management, the integration of AI solutions into business processes, the development of the risk management system, and the ability to use AI to support and shape strategic decisions. On this basis, a conceptual model is proposed that provides for a consistent transition from experimental and operational use of AI to its integration into the strategic financial management system (Figure 2).

The proposed model defines five sequential maturity levels of artificial intelligence (AI) use in finance, from local experimentation with individual AI solutions to strategic integration of artificial intelligence into the management system and the formation of competitive advantages. The model allows assessing not only the fact of using technologies, but also the degree of their integration into business processes, data management systems, risks, and management decision-making.

The main features of the first level are the lack of a single AI strategy, standardized approaches to performance assessment, and systematic risk management. The result is the accumulation of primary experience and awareness of the possibilities of applying AI. The second level – operational (AI Adoption) – means the transition from experimentation to practical use of AI to automate specific operations. At this level, the basic AI infrastructure is formed, responsible employees are identified, and a systematic assessment of the economic effect begins.

AI solutions cease to function as separate technology projects and are integrated between departments and corporate information systems at the third level. Centralized data management, model quality monitoring, model drift control, cyber risks, and regulatory compliance are of particular importance here. At this stage, AI begins to influence not only operational processes, but also tactical management decisions.

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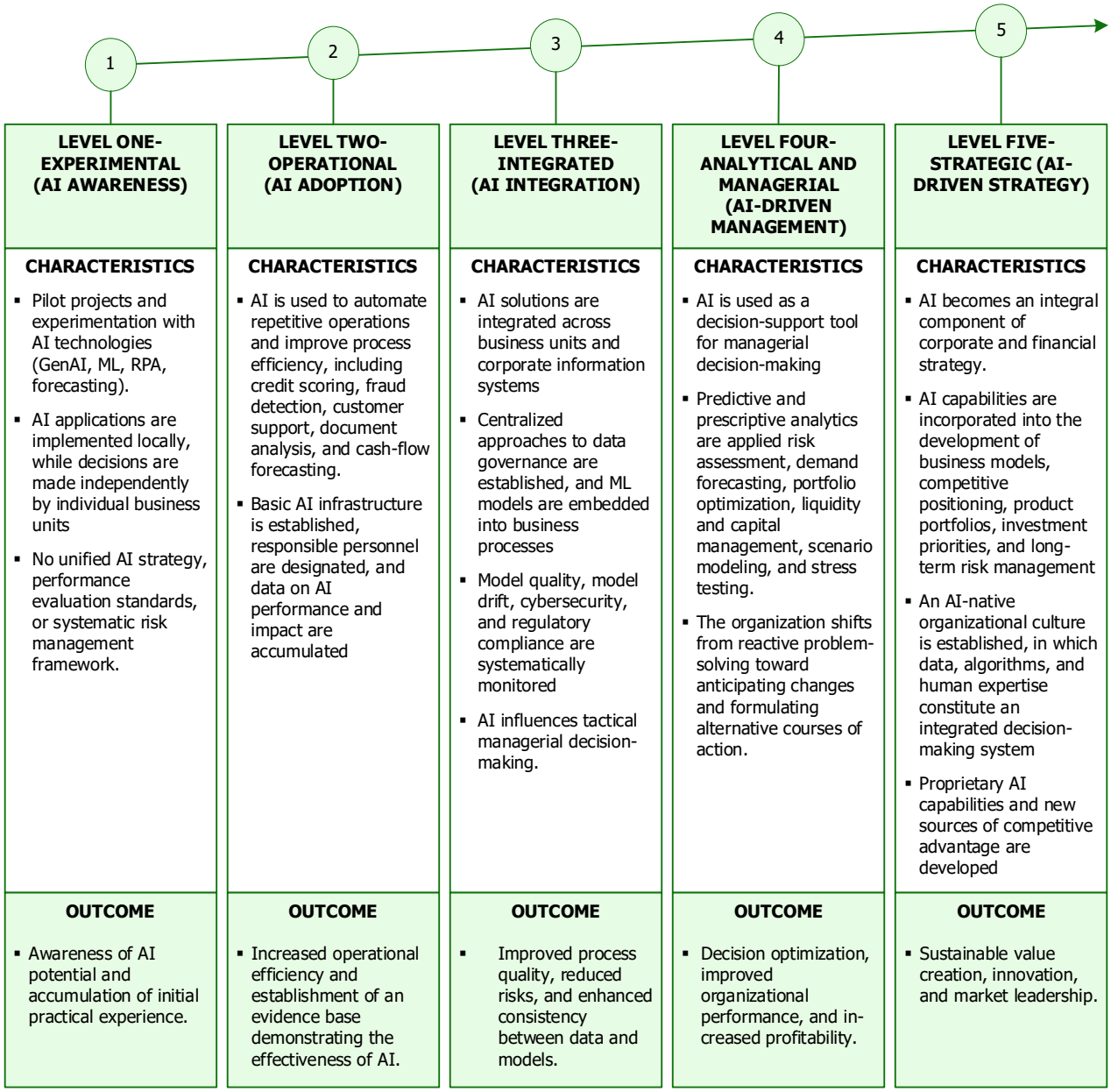


Figure 2. Conceptual model of maturity levels of AI application in the financial sector.

The fourth level - analytical and managerial (AI-Driven Management) involves using AI directly to support management decisions, moving to predictive and prescriptive analytics, using AI for risk assessment, demand forecasting, portfolio optimization, liquidity and capital management, scenario modeling, and stress testing. A key characteristic is the transition from reactive to proactive management, where analytical systems allow not only to identify problems, but also to predict future changes and form alternative courses of action. At the highest, strategic level of maturity, AI becomes an integral part of corporate and financial strategy. AI capabilities are taken into account when forming the business model, competitive position, product portfolio, investment priorities, and long-term risk management policy. An AI-native culture is being formed, within which data, algorithms, and human expertise form a single decision-making system. The financial sector is moving from adapting off-the-shelf technologies to developing its own AI competencies, creating innovative products, and building long-term competitive advantages.

Therefore, the proposed model demonstrates that the AI maturity of the financial sector is a multidimensional process that is not limited to the number of technologies implemented. It is determined by the level of integration of AI into business processes, the quality of data management, organizational readiness, risk management systems, the ability to use predictive analytics, and the role of AI in strategic management. The logic of the model involves a sequential transition from technological experimentation to strategic transformation. At the first two levels, the focus is on gaining experience and improving operational efficiency. The third level ensures system integration of technology and risk management. The

fourth translates AI into the realm of management analytics, and the fifth into the realm of forming business strategy and competitive advantages.

It is important to clarify that the proposed levels characterize not an individual AI tool or the most complex case of its application, but the overall degree of AI institutionalization within an organization. Therefore, the use of a sophisticated AI model in a single local process is not sufficient grounds for assigning an enterprise to a higher maturity level. Level 3 is defined by the systematic integration of AI solutions into business processes, data, and information systems; Level 4 by the direct use of AI outputs for forecasting, scenario analysis, and managerial decision-making; and Level 5 by the incorporation of AI capabilities into business model development, long-term strategy, and competitive positioning. At the same time, the technological sophistication of an AI solution does not compensate for the absence of adequate data governance, model oversight, human supervision, and accountability. Therefore, AI autonomy should not be equated with AI maturity, while isolated cases of unauthorized or uncontrolled use of AI should be regarded as manifestations of AI governance risk rather than indicators of a higher level of maturity.

It is important that the transition between levels should not be seen solely as a technological improvement. It involves the simultaneous development of organizational structure, personnel competencies, corporate culture, data management systems, and AI risk management mechanisms. In general, the model can be presented as moving through five key stages: "experimentation → operational application → integration → management analytics → strategic transformation" (Crisanto, 2026). Each subsequent level is characterized by an increase in the scale of AI use, the complexity of management tasks, the level of integration, and the potential economic effect.

Thus, the proposed model can be used as a diagnostic and strategic assessment tool for AI maturity. It helps determine the current level of development, identify organizational and technological gaps, form priorities for further digital transformation, and determine the directions of transition to a higher level of AI use. The end result of such a transition should not simply be the automation of individual operations, but the formation of an integrated system of "data - algorithms - human expertise - management decisions" capable of ensuring the sustainability, innovation, and long-term competitiveness of a financial institution.

Therefore, the transition between maturity levels (Figure 2) is not a purely technological issue. It is accompanied by three interrelated processes:

- firstly, the complexity of models – from transparent statistical methods to deep learning, which requires the development of explainability tools;
- secondly, by expanding the circle of people who make decisions based on AI recommendations, from analysts to top management;
- thirdly, increasing requirements for regulatory compliance and transparency of models as we approach the strategic level of decision-making.

Thus, the maturity of AI application is determined by the transition from "using technology" to "transforming management through technology." If at the first two levels the main criterion for effectiveness is the reduction of costs and time for performing operations, then at the strategic level the contribution of AI to generating income, increasing sustainability, optimizing risks, creating new financial products, and long-term competitiveness is assessed. For practical assessment of maturity, it is advisable to use a system of criteria along five dimensions: technological (data, models, IT infrastructure); organizational (AI competencies, responsibility structure, culture); managerial (integration of AI into decision-making processes); risk and regulatory (model risk management, explainable AI, cybersecurity, data protection and compliance with regulatory requirements); strategic (impact of AI on the business model, innovation and competitive advantages).

DISCUSSION

The results obtained confirm the trend in modern scientific literature towards a qualitative transformation of the role of artificial intelligence in the financial sector - from a tool for automating individual operations to a component of a system of management and strategic decisions. The historical and logical analysis conducted provides grounds to consider this transformation as a sequential process of transition from rule-based systems to machine learning, deep learning, and generative AI. This conclusion is consistent with the results of studies that characterize the current development of the financial sector through the expansion of the spectrum of applications of AI/ML from credit scoring, fraud detection, and algorithmic trading to asset management, insurance, payments, and strategic analytics (Cao, 2022; Aldasoro, 2024).

At the same time, the results of the study allow us to clarify the traditional understanding of the technological evolution of AI. It has been established that the complexity of models does not in itself provide an increase in the level of managerial

DOI: 10.55643/fcaptp.5.70.2026.5313

influence. In particular, a high level of automation is characteristic of areas such as fraud detection, AML/KYC, and algorithmic trading, but this does not mean that a financial institution automatically moves to a strategic level of AI use. Instead, the strategic value arises when the results of the models are integrated into the processes of forming and implementing financial strategy, scenario analysis, resource allocation, and long-term risk management. Therefore, the maturity criterion proposed in the study – the degree of integration of AI into the management system – is more meaningful than the number of models used or the level of their technological complexity.

This conclusion complements the results of previous studies, which focused on individual functional areas of AI application. Credit risk research demonstrates the potential of ML models to improve the accuracy of default prediction, while systemic risk research demonstrates the capabilities of machine learning to account for a broader range of macroeconomic variables. At the same time, the results of the study confirm that increasing predictive efficiency should be accompanied by the development of mechanisms for model control, explainability, and human oversight (Wilson, 2025). Thus, technological performance and managerial reliability of AI should be considered as interrelated, but not identical, characteristics.

The problem of explainability of models becomes of particular importance. The analysis showed that the transition to more complex machine and deep learning models is accompanied by an increase in the "black box" problem. In the financial sector, this problem is not only technical, but also managerial and regulatory in nature, since decisions regarding lending, insurance, investments, or the detection of suspicious transactions can directly affect the rights and financial interests of customers. Therefore, the use of Explainable AI should not be considered as an additional technological function, but as a component of a corporate model management system. This is consistent with the findings of modern XAI research, which emphasize the need to combine the accuracy of algorithms with the ability to interpret and verify the obtained results (Černevičienė, 2024; Weber, 2024).

The emergence of generative AI and large language models requires special attention. Unlike traditional predictive systems, GenAI extends AI functionality by working with unstructured information, text generation, document analysis, scenario modeling, and natural language communication. This creates the prerequisites for AI to move to the strategic level. At the same time, the results of the study confirm that generative AI cannot be considered an autonomous substitute for management expertise. The quality of its recommendations depends on the quality of the data, the task, the context, and the user's ability to verify the results obtained. Therefore, the strategic application of GenAI requires a human-in-the-loop model, in which the ultimate responsibility for critical financial decisions remains with authorized individuals.

The proposed five-level maturity model allows combining the technological and managerial dimensions of AI transformation. Its fundamental difference is that the transition between levels is determined not only by the expansion of AI functionality, but also by the simultaneous development of data governance, model governance, human oversight, and strategic integration. This approach expands the traditional interpretation of digital maturity, as it shifts the focus from technological support to the ability of an organisation to manage technology and transform its results into economically sound solutions.

The results of the risk classification also indicate the need for a comprehensive approach to AI risk management. Technological risks, data quality issues, regulatory restrictions, reputational damage, ethical issues, and systemic risks are interrelated. At the initial levels of maturity, risks of data quality and technical reliability of models dominate, while with the transition to the strategic level, the importance of risks of liability, concentration of technology providers, interdependence of models and the potential impact of algorithmic errors on financial stability increases. This pattern is consistent with the conclusions of the Financial Stability Board regarding the potential systemic impact of AI/ML on the financial system.

For Ukraine, the results have particular practical significance. Limited resources to develop their own complex AI solutions increase the dependence of financial institutions on external platforms, cloud services, and technology providers. Under such conditions, strategic maturity should include not only internal technological competence, but also data control, assessment of supplier dependence, ensuring cybersecurity, and compliance with European regulatory requirements. At the same time, Ukrainian scientific discourse demonstrates a gradual shift in attention from general digitalization to assessing the impact of AI on financial stability, risk management, the competitive environment, and the strategic consequences of its use.

Thus, the results of the study give reason to argue that the main problem of the current stage of AI transformation is not a shortage of technological capabilities, but the insufficient organizational readiness of financial institutions to use these capabilities at a strategic level. That is why the transition from operational to strategic use of AI requires the synchronous development of technological infrastructure, data management systems, model risk management, personnel competencies, human control mechanisms, and corporate governance.

CONCLUSIONS

According to the results of a study of the evolution of the application of artificial intelligence technologies in the financial sector, it was found that its development is not linear, but sequentially transformational in nature and reflects a change in the functional role of intelligent technologies in the financial management system. The generalization of theoretical approaches and modern practices of using AI made it possible to distinguish four main stages of its evolution: algorithmic-rule, machine learning, deep learning, and generative-strategic. Each of these stages is characterized by a specific level of technological complexity, the nature of information processing, the degree of autonomy of algorithms, and the scale of their impact on management processes. It has been established that the key trend in the evolution of AI in finance is the gradual transition from the automation of individual operations to the intellectualization of management processes. If in the early stages the main criterion for efficiency was the speed and accuracy of performing standardized operations, the modern stage is characterized by the increasing importance of predictive, recommendatory, and strategic functions of AI. This gives reason to consider the modern transformation of the financial sector not only as a technological update, but as a structural change in the nature of financial management, within which AI is gradually moving from an auxiliary information processing tool to a component of the corporate governance system.

A limitation of the methodology used is that it does not provide for a quantitative assessment of the economic effect of implementing artificial intelligence in specific financial institutions, since such data is mostly confidential and unavailable for open scientific analysis. Instead, the emphasis is on qualitatively summarizing existing experience and building a conceptual model that can serve as a basis for further quantitative research.

At the same time, it is advisable to consider AI in financial activities not only in terms of functional purpose, but also in terms of the level of managerial influence. The analysis allowed us to identify the following main areas: credit scoring and solvency assessment; fraud detection; AML/KYC procedures; algorithmic trading; investment portfolio management; forecasting of financial indicators; automation of customer service; personalization of financial products; risk management; financial planning; scenario analysis; strategic forecasting and support of management decisions. Thus, at the operational level, AI is mainly used to automate standardized procedures, process large amounts of information, identify customers, detect suspicious transactions, automate customer service, and optimize internal processes. The tactical level of AI application is associated with supporting decisions regarding credit policy, risk management, investment portfolio formation, demand forecasting, customer segmentation, and optimization of financial products. In this case, algorithms not only perform operations, but also form an information and analytical basis for choosing alternative options for management actions. At the strategic level, AI is used for long-term forecasting, scenario modeling, assessing market development prospects, forming business models, determining competitive positions, and supporting strategic planning. At the same time, it has been established that this area remains the most complex from an organizational point of view, as it involves the integration of AI solutions with the corporate governance system, strategic planning, risk management, and control.

Therefore, the results of the study indicate that the vast majority of modern AI solutions in the financial sector are still focused on the operational and tactical levels, while strategic application is in the stage of active formation. At the same time, it is fundamental that the level of managerial effect is determined not so much by the complexity or technological novelty of the algorithm, but by the degree of its integration into the process of making managerial decisions. That is, using a complex model without incorporating its results into the management system may have a smaller economic effect than using a relatively simple algorithm that is organizationally integrated, controlled, and linked to specific management procedures.

Based on the results of the study, a conceptual model of maturity levels of AI application in the financial sector has been developed, which reflects AI maturity as a comprehensive characteristic of the abilities of a financial institution to systematically create, implement, control, and scale intelligent technologies, taking into account their economic, managerial, legal, and risk consequences. The proposed approach is based on the assumption that the technological implementation of AI in itself does not ensure the transition of a financial institution to a new qualitative level of management.

Therefore, the results obtained confirm that the transformation of the role of AI in the financial sector is taking place in the direction of a gradual transition from automation and analytical support to the intellectualization of strategic management. However, technological progress is not a sufficient condition for such a transition. It is essential to form an appropriate institutional environment, organizational competencies, a data and model management system, control mechanisms, and responsible use of algorithmic technologies. The scientific significance of the results obtained lies in the complex combination of evolutionary, functional, risk, and managerial approaches to the study of AI in finance. This approach allows us to move from a fragmentary analysis of individual AI technologies to an assessment of the process of forming a holistic AI maturity system of a financial institution. The practical significance of the proposed model lies in the possibility

DOI: 10.55643/fcaptp.5.70.2026.5313

of its use by financial institutions to diagnose the current level of AI maturity, identify technological and organizational gaps, form a digital transformation roadmap, and determine priority areas for investment in relevant technologies. This is of particular importance for banks, insurance companies, investment companies, financial technology companies, and other financial market participants.

Prospects for further research are primarily related to the quantitative operationalization of the proposed AI maturity model, the development of a system of indicators for its measurement, and empirical testing on a sample of banks, insurance companies, fintech companies, and other financial institutions. It is advisable to form an integral AI maturity index, which will allow quantitatively assessing the technological, organizational, managerial, and regulatory components of an institution's readiness for the strategic use of AI. A particularly promising direction is to determine the statistical relationship between the level of AI maturity and indicators of financial efficiency, operational performance, risk, financial stability, and competitiveness. This creates the basis for moving from conceptual justification of the benefits of AI to their quantitative assessment and determination of the real economic effect of the strategic integration of intelligent technologies.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

FUNDING

The Authors received no funding for this research.

CONFLICT OF INTEREST

The Authors declare that there is no conflict of interest.

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РЕВОЛЮЦІЯ ШТУЧНОГО ІНТЕЛЕКТУ У ФІНАНСАХ: ВІД АЛГОРИТМІВ ДО СТРАТЕГІЧНИХ РІШЕНЬ

Стрімкий розвиток технологій штучного інтелекту (ШІ) трансформує фінансовий сектор, змінюючи підходи до автоматизації операцій, аналізу великих масивів даних, прогнозування, управління ризиками, обслуговування клієнтів

DOI: 10.55643/fcaptp.5.70.2026.5313

та ухвалення управлінських рішень. Актуальність дослідження зумовлена необхідністю переходу від фрагментарного та переважно операційного використання алгоритмічних інструментів до їх системної інтеграції в стратегічне управління у фінансах. Метою дослідження є систематизація напрямів застосування ШІ у фінансовій царині та обґрунтування концептуальної моделі переходу від операційного використання алгоритмічних інструментів до стратегічного рівня управління. Для досягнення поставленої мети застосовано системний, історико-логічний, порівняльний і класифікаційний методи. Основні результати дослідження полягають у визначенні чотирьох етапів еволюції застосування ШІ у фінансах: алгоритмічно-правилового, машинного навчання, глибокого навчання та генеративно-стратегічного. Систематизовано ключові напрями використання ШІ за рівнем управлінського впливу – від автоматизації рутинних операцій і підтримки окремих бізнес-процесів до прогнозування, управління ризиками, персоналізації фінансових послуг і формування стратегічних управлінських рішень. Узагальнено технологічні, регуляторні, репутаційні, етичні та системні ризики, пов'язані з масштабуванням ШІ у фінансовому секторі. Запропоновано п'ятирівневу модель зрілості застосування ШІ, яка передбачає послідовний перехід від експериментального, операційного й інтегрованого рівнів до рівня управлінської трансформації та стратегічного використання технологій.

Зроблено висновок, що стратегічна цінність ШІ визначається не кількістю впроваджених технологічних рішень, а ступенем їх інтеграції в систему корпоративного управління, якістю й доступністю даних, ефективністю управління моделями, компетентностями персоналу, пояснюваністю алгоритмічних рішень, дотриманням регуляторних вимог і результативністю контролю ризиків. Стратегічна інтеграція ШІ створює передумови для підвищення адаптивності, конкурентоспроможності й стійкості фінансового сектора.

Ключові слова: штучний інтелект, фінансові технології, алгоритмічна торгівля, машинне навчання, пояснюваний штучний інтелект, ризик-менеджмент, стратегічне управління, фінтех

JEL Класифікація: G10, G20, G32, C45, C55, O33