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ARTIFICIAL INTELLIGENCE IN FINANCIAL RISK ANALYSIS: THEORY AND PRACTICE

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ИСКУССТВЕННЫЙ ИНТЕЛЛЕКТ В АНАЛИЗЕ ФИНАНСОВЫХ РИСКОВ: ТЕОРИЯ И ПРАКТИКА

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Abstract

This article focuses on the application of artificial intelligence (AI) in financial risk analysis and management. It explores the main methods of integrating AI into stress testing and scenario modeling processes, as well as its impact on improving forecast accuracy and decision-making under uncertainty. Special attention is given to the use of machine learning and deep learning algorithms for analyzing large datasets, identifying hidden patterns, and simulating risks, including rare but highly impactful events («black swans»). The article discusses the advantages of AI in enhancing the adaptability of systems to changing market conditions and in improving the speed of decision-making. It also addresses challenges related to data quality, the need for algorithm transparency, as well as ethical considerations and regulatory compliance. In conclusion, the article highlights the importance of further AI development in the financial sector and its role in improving the resilience of financial institutions in the face of global economic instability.

Keywords: artificial intelligence, financial risks, stress testing, scenario modeling, machine learning, deep learning, risk management, financial resilience, «black swans», algorithms.

Аннотация

Статья посвящена применению искусственного интеллекта (ИИ) в анализе и управлении финансовыми рисками. В статье рассматриваются основные способы интеграции ИИ в процессы стресс-тестирования и сценарного моделирования, а также его влияние на точность прогнозов и принятие решений в условиях неопределенности. Особое внимание уделено использованию алгоритмов машинного обучения и глубокого обучения для анализа больших объемов данных, выявления скрытых закономерностей и моделирования рисков, включая редкие, но высоко вероятные события («черные лебеди»). В статье обсуждаются преимущества ИИ в улучшении адаптивности систем к изменениям рыночных условий и в повышении оперативности принятия решений. Также рассматриваются вызовы, связанные с качеством данных, необходимостью обеспечения прозрачности алгоритмов, а также вопросами этики и соблюдения регуляторных стандартов. В заключение подчеркивается важность дальнейшего развития ИИ в финансовом секторе и его роль в повышении устойчивости финансовых институтов в условиях глобальной экономической нестабильности.

Ключевые слова: искусственный интеллект, финансовые риски, стресс-тестирование, сценарное моделирование, машинное обучение, глубокое обучение, управление рисками, устойчивость финансовых институтов, «черные лебеди», алгоритмы, большие данные.

Introduction

The rapidly evolving landscape of financial markets has highlighted the growing need for more advanced tools in financial risk analysis. Traditionally, financial institutions have relied on statistical methods and human judgment to assess and manage risk. However, as the complexity and volume of data continue to increase, these traditional approaches are often no longer sufficient. Artificial intelligence offers promising solutions by providing powerful tools to process vast amounts of data quickly and accurately, enabling financial institutions to identify and mitigate risks more effectively than ever before. This shift from traditional methods to AI-driven solutions marks a significant transformation in how financial risks are understood and managed.

The potential of artificial intelligence in financial risk analysis lies in its ability to handle complex, high-dimensional data and learn from patterns that traditional models might miss. AI algorithms, particularly machine learning (ML) and deep learning (DL) models, are capable of making predictions based on historical data, identifying correlations, and detecting outliers that could indicate emerging risks. In the context of financial markets, where data is constantly changing and evolving, AI systems can provide real-time risk assessments, allowing for more timely and informed decision-making. This ability to adapt to new information and improve over time is what sets AI apart from traditional risk management tools, which often rely on static models.

Despite the promising potential, the application of AI in financial risk analysis is not without challenges. The use of AI requires vast amounts of data, and the quality of that data is crucial for generating accurate predictions. Moreover, there are concerns regarding the transparency of AI models, particularly with complex algorithms that function as «black boxes». This lack of transparency can create barriers in regulatory environments that demand accountability and explainability in decision-making processes. Additionally, the integration of AI in financial risk analysis raises ethical questions about data privacy, bias, and the potential displacement of human workers in financial institutions.

The goal of this article is to explore the role of artificial intelligence in financial risk analysis, examining both the theoretical foundations and the practical applications of AI technologies in the financial sector. By analyzing current trends and challenges, this article aims to provide a comprehensive overview of how AI can be used to enhance risk prediction, improve decision-making, and address emerging financial risks. The study also seeks to highlight the barriers that need to be overcome for the widespread adoption of AI in financial risk management, and the potential implications of this technology for the future of the industry.

Main part. AI models in financial risk prediction

The integration of artificial intelligence into financial risk prediction has proven to be a game-changer, offering more precise, data-driven insights compared to traditional methods. Financial risk prediction involves identifying potential hazards that can impact an organization's financial stability. This includes credit risk, market risk, operational risk, and liquidity risk. While traditional methods primarily relied on statistical models and human judgment, AI-driven techniques allow for faster and more accurate identification of emerging risks. Machine learning and deep learning algorithms, for instance, can analyze large datasets in real time, identifying patterns and anomalies that humans might overlook [1].

AI models used in financial risk prediction often involve supervised learning algorithms, which are trained on historical data to make predictions about future events. One popular approach is the use of random forests, which combine multiple decision trees to make more reliable predictions by reducing the risk of overfitting. Another widely used method is support vector machines, which are effective in finding patterns in data and can be particularly useful for classifying financial transactions as either risky or non-risky. Neural networks, particularly deep neural networks, are another key technology in risk prediction, especially in high-dimensional data such as financial markets, where complex relationships exist between variables.

The application of AI in risk prediction can significantly improve the accuracy and efficiency of financial decision-making [2]. However, challenges remain in selecting the appropriate model and ensuring the quality of the data. Not all AI models are equally effective across different types of

financial risks, and the choice of algorithm should reflect the specific requirements of the analysis. Additionally, financial institutions must be cautious about potential biases in training data, which can compromise model outcomes. To provide a clearer understanding of the comparative strengths of different AI models, figure 1 presents a performance-based comparison focused on accuracy, processing speed, and interpretability.
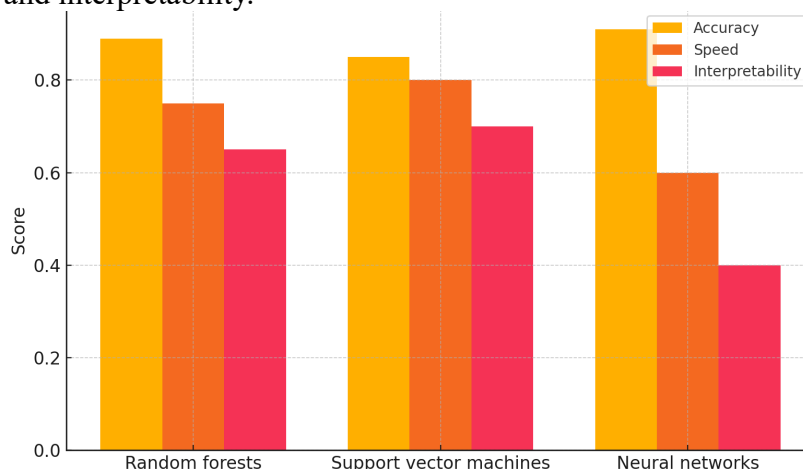

Figure 1. Performance comparison of AI models in financial risk prediction

Figure illustrates a comparative analysis of three commonly used AI models-random forests, support vector machines, and neural networks-based on their performance in terms of accuracy, processing speed, and interpretability. Neural networks demonstrate the highest accuracy among the models, making them suitable for complex, high-dimensional financial data. However, they score the lowest in interpretability, which may limit their applicability in regulated environments where model transparency is essential [3]. Support vector machines offer a balanced trade-off between speed and accuracy, while random forests provide a strong combination of performance and moderate interpretability. These distinctions underscore the importance of selecting a model that aligns with the specific objectives and regulatory constraints of financial risk analysis.

In practice, the selection of an AI model for financial risk prediction depends not only on its performance characteristics but also on the operational and regulatory context in which it is deployed. For instance, while neural networks may offer superior accuracy, their limited interpretability can be a significant drawback in sectors that require transparency and auditability of decision-making processes. This is particularly relevant in regulatory environments where explanations for automated decisions are mandated by law or internal governance frameworks.

In contrast, models such as random forests and support vector machines provide a more favorable balance between predictive power and interpretability. Random forests, due to their ensemble nature, allow partial insight into decision pathways by evaluating the contribution of individual features across trees. Support vector machines, while less transparent in structure, still offer a level of analytical traceability that exceeds that of deep learning architectures. These attributes make them suitable for applications where both predictive accuracy and explanatory power are critical, such as in credit scoring or operational risk assessments [4].

The ongoing development of hybrid models and explainable AI (XAI) techniques aims to address the trade-offs between performance and interpretability. For example, researchers are exploring methods to approximate the outputs of complex models using simpler surrogate models that can be inspected and interpreted by human analysts. Such techniques enable institutions to benefit from the superior accuracy of advanced AI systems while maintaining compliance with governance and transparency requirements. As these tools mature, the integration of high-performing AI models into financial risk frameworks is expected to become more widespread and robust.

Data requirements and preprocessing in AI-driven risk analysis

One of the foundational elements determining the success of AI applications in financial risk analysis is the availability and quality of data. Unlike traditional models that may rely on a limited number of structured variables, AI models, particularly those based on machine learning, require large volumes of high-dimensional data to function effectively. These datasets may include structured data

such as financial statements and transaction records, as well as unstructured data sources like social media feeds, news articles, and regulatory reports. The ability of AI systems to handle such varied inputs offers greater flexibility and insight, but it also imposes stringent demands on data integrity and preprocessing [5].

Data preprocessing plays a critical role in preparing information for AI-based analysis. Financial data is often noisy, incomplete, or inconsistent due to reporting delays, human error, or incompatible data formats. As a result, preprocessing steps such as normalization, imputation of missing values, outlier detection, and feature engineering are essential to ensure that models receive reliable inputs. These processes help to minimize distortions in model training and contribute to the development of robust, generalizable algorithms. Moreover, the choice of features and how they are encoded can significantly influence the model's ability to detect patterns and make accurate predictions.

Another important consideration is the ethical handling of sensitive financial information. Given the volume of personal and transactional data involved in AI-based financial analysis, compliance with data protection regulations such as the General Data Protection Regulation (GDPR) and other jurisdiction-specific laws is essential. Institutions must ensure that data is collected, stored, and processed with proper consent and safeguards in place. Furthermore, the use of biased or unbalanced datasets can result in unfair or discriminatory outcomes, particularly in credit risk assessment or fraud detection scenarios. Therefore, institutions must not only focus on the technical aspects of data preparation but also incorporate governance frameworks that promote fairness, accountability, and transparency in AI-driven risk analytics.

Beyond basic preprocessing, the automation of data handling through AI-based data pipelines has become an essential aspect of modern risk analytics workflows. These automated systems are capable of detecting anomalies, correcting formatting inconsistencies, and flagging missing values without the need for extensive manual intervention. By integrating AI into the data preparation phase itself, institutions can significantly reduce time-to-deployment for new models and ensure greater consistency across analyses [6]. This automation not only enhances efficiency but also minimizes the potential for human-induced errors that could distort financial predictions.

Equally important is the process of feature selection, which determines the specific variables that will be used to train the AI models. In financial contexts, selecting features that are both informative and non-redundant is critical, as irrelevant or highly correlated features can introduce noise and decrease model accuracy. Advanced techniques such as recursive feature elimination, LASSO regularization, or information gain ranking are frequently employed to optimize input variables. The outcome of this process has a direct effect on the explainability and performance of risk prediction models. Poorly selected features may cause models to overlook essential signals or over fit to spurious patterns, ultimately leading to inaccurate risk assessments and strategic misjudgments.

The consequences of inadequate data preprocessing can be severe, particularly in high-stakes financial environments. Inaccuracies introduced through missing values, mislabeled categories, or unfiltered outliers may result in flawed model training, which in turn can lead to erroneous risk classifications. For example, an underreported exposure in a portfolio dataset could cause a model to underestimate potential credit risk, leading to poor capital allocation and increased vulnerability to default events. Similarly, unbalanced datasets-where one class, such as "low risk," is overrepresented-can bias the model's learning process, reducing its ability to correctly identify rare but critical high-risk cases [7]. These issues underscore the necessity of a meticulous approach to data curation, emphasizing not only volume but also accuracy, representativeness, and ethical integrity in all phases of AI-driven risk analysis.

Real-time risk monitoring and visualization with AI tools

The adoption of artificial intelligence in financial risk management has enabled organizations to move beyond periodic risk assessments toward real-time risk monitoring [8]. AI-powered systems can continuously analyze streaming data from a wide variety of sources, such as trading platforms, news feeds, and economic indicators, to identify emerging threats and opportunities. This real-time

capability is crucial in modern financial markets, where rapid changes can have significant consequences for portfolios, liquidity, and compliance.

One of the key advancements supporting real-time monitoring is the use of AI-driven dashboards and visualization tools. These platforms integrate data from multiple channels, process it using advanced analytics, and present the results in a clear and actionable format. Visual representations of risk metrics, such as heat maps, time series graphs, or alert systems, enable decision-makers to quickly grasp the current risk landscape and respond promptly to new developments. The value of such visualization tools lies in their ability to translate complex data streams into intuitive insights, facilitating faster and more informed decision-making [9].

Figure 2 illustrates a conceptual layout of an AI-driven real-time risk monitoring dashboard. The schematic includes key components such as portfolio exposure, market volatility, risk score trends, and news sentiment analysis, all of which contribute to continuous risk assessment. Additionally, a dedicated alert section highlights thresholds and triggers for rapid incident detection, while supplementary metrics provide deeper contextual insights such as liquidity levels and counterparty risk exposure.
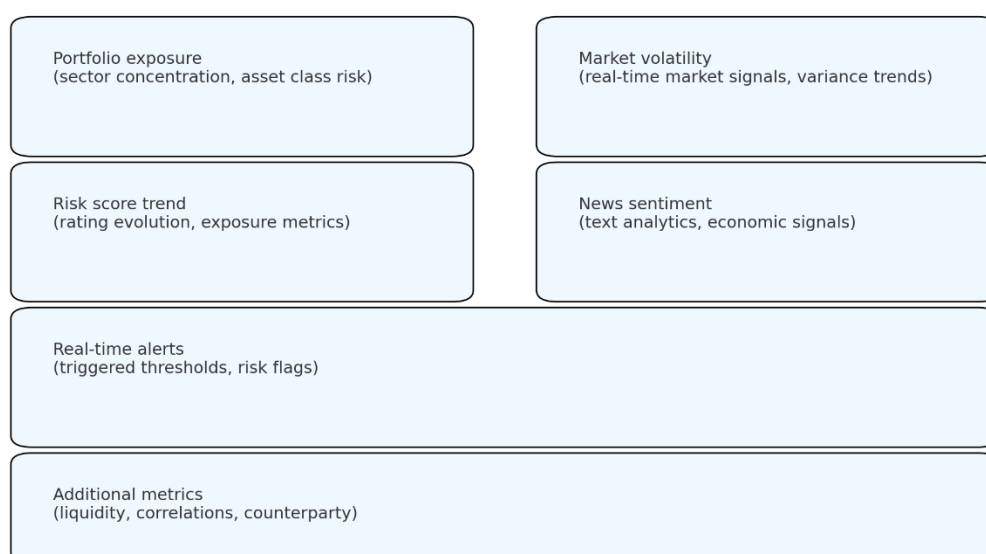

Figure 2. AI-driven real-time risk monitoring dashboard

This form of integrated visualization allows financial institutions to unify various risk indicators into a coherent and accessible format. By combining analytical precision with interpretability, these dashboards enhance the responsiveness and agility of risk management teams, ultimately improving the institution's resilience to sudden market changes.

The practical implementation of AI-driven dashboards has already demonstrated tangible benefits across various financial institutions. For instance, investment banks utilize real-time dashboards to track intraday market fluctuations, instantly visualizing the impact of macroeconomic news or geopolitical events on portfolio risk levels. Similarly, credit institutions deploy internal AI dashboards to monitor borrower profiles and early warning indicators, enabling proactive adjustments to credit limits and exposure. These systems are often integrated with internal risk management platforms and data warehouses, allowing seamless updates and centralized oversight. By reducing reliance on manual reporting and static spreadsheets, AI-based dashboards significantly shorten response times and help institutions maintain operational readiness in dynamic environments.

Scenario simulation and stress testing using AI algorithms

In the face of increasing market volatility, regulatory pressure, and geopolitical instability, scenario simulation and stress testing have become indispensable tools in financial risk management. These methods enable institutions to evaluate the resilience of their portfolios under hypothetical adverse conditions. Traditionally, stress testing relied on historical data and predefined economic scenarios. However, the complexity of modern financial systems and the growing volume of data necessitate more dynamic and intelligent approaches. Artificial intelligence offers a powerful

enhancement to conventional methods, enabling the generation, execution, and interpretation of stress scenarios with unprecedented speed and granularity.

AI-based scenario simulation involves the use of predictive models to create synthetic events that go beyond historical precedent. These models can incorporate a wide array of variables - including macroeconomic indicators, liquidity patterns, counterparty exposure, and behavioral signals - to estimate portfolio responses under multiple risk pathways. Machine learning models are particularly well-suited to this task, as they can identify nonlinear relationships among variables and update their parameters continuously based on incoming data. This adaptability makes AI an ideal tool for forecasting under uncertainty and modeling the compounding effects of simultaneous shocks.

Moreover, deep learning techniques are increasingly employed to simulate extreme but plausible events, often referred to as "black swan" scenarios. These systems analyze massive datasets, including unstructured text from financial news and central bank reports, to anticipate hidden correlations and emergent risks. This allows institutions not only to test their exposure under predefined shocks but also to explore new, unobserved threat combinations. For example, stress testing models can simulate the joint impact of interest rate spikes, supply chain disruptions, and climate-related shocks, providing a more comprehensive view of institutional vulnerability.

Figure 3 illustrates a sample stress-testing output where a hypothetical event in month 7 triggers a significant deviation from the baseline portfolio trajectory. While the baseline scenario indicates steady growth, the AI-modeled stress scenario shows a sharp decline followed by a slower recovery. This visualization highlights the potential impact of an adverse event on portfolio stability and underscores the importance of preparedness for compound risk events.
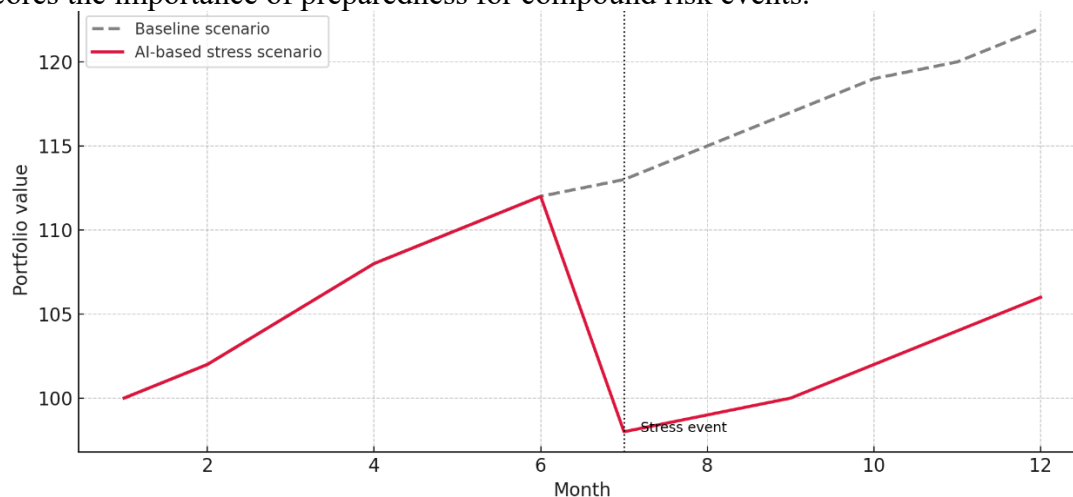

Figure 3. AI-based stress testing output for portfolio value

In addition to modeling «black swan» events, AI also excels in simulating a wide range of other complex, real-world scenarios that financial institutions are likely to face. One such application is the simulation of cascading risks across interconnected sectors and markets. For instance, the outbreak of a geopolitical crisis or the collapse of a major financial institution can trigger a chain reaction that affects various asset classes, from equities to bonds and commodities. Traditional stress-testing methods often struggle to capture such interdependencies. In contrast, AI algorithms, especially those based on neural networks, can identify and model these relationships, providing institutions with more accurate forecasts of the potential ripple effects of a crisis.

Furthermore, AI-driven models can take into account emerging data sources such as social media sentiment or news articles, offering real-time insights into market movements and risk sentiment [10]. For example, by analyzing the sentiment in financial news and public reports, AI can detect early warning signs of financial instability, such as negative shifts in investor confidence or signs of an impending economic downturn. This level of real-time analysis is invaluable for risk managers, who can use it to adjust their portfolios dynamically and mitigate potential risks before they materialize.

AI's capacity for continuous learning further enhances the effectiveness of scenario simulation and stress testing. As new data becomes available, AI models can adjust their predictions in real time,

improving their accuracy over time. This dynamic adjustment is particularly important in fast-moving financial markets, where historical models may fail to capture rapidly evolving trends. Moreover, AI-based models can simulate a range of different risk factors simultaneously, such as interest rates, inflation, and currency fluctuations, providing a more holistic view of portfolio risk.

Conclusion

The integration of artificial intelligence into financial risk analysis has revolutionized the way financial institutions assess, predict, and mitigate risks. By leveraging machine learning, deep learning, and other AI-based techniques, companies can now simulate complex scenarios, predict potential vulnerabilities, and assess their portfolios under a wide range of conditions that traditional methods might overlook. AI's ability to process vast amounts of data in real time and adapt to emerging risks provides financial institutions with a more agile and accurate risk management framework, enabling quicker responses to sudden market shifts or unforeseen events.

However, the application of AI in financial risk management is not without its challenges. Data quality, transparency of algorithms, and the integration of AI into existing risk management structures remain key concerns. Financial institutions must navigate these challenges carefully to ensure that AI-driven models are both accurate and ethically sound. Furthermore, the complexity of AI models often requires an ongoing commitment to model validation and regulatory compliance, which can add layers of complexity to the integration process.

Despite these hurdles, the future of AI in financial risk analysis looks promising. As AI technologies continue to evolve, they will become increasingly sophisticated and capable of handling even more complex financial scenarios. The use of AI in scenario simulation, stress testing, and real-time risk monitoring will continue to provide valuable insights for decision-makers, enhancing the resilience of financial institutions in an increasingly volatile global market. Moving forward, it is essential for financial institutions to embrace these advanced technologies, while maintaining rigorous standards for data management, transparency, and regulatory compliance, to fully harness the potential of AI in financial risk management.

References

1. Li Y., Yi J., Chen H., Peng D. Theory and application of artificial intelligence in financial industry // Data Science in Finance and Economics. 2021. Vol. 1. No. 2. P. 96-116.
2. El Hajj M., Hammoud J. Unveiling the influence of artificial intelligence and machine learning on financial markets: A comprehensive analysis of AI applications in trading, risk management, and financial operations // Journal of Risk and Financial Management. 2023. Vol. 16. No. 10. P. 434.
3. Milojević N., Redzepagic S. Prospects of artificial intelligence and machine learning application in banking risk management // Journal of Central Banking Theory and Practice. 2021. Vol. 10. No. 3. P. 41-57.
4. Medina-Vidal A., Alonso-Galicia P.E., González-Mendoza M., Ramírez-Montoya M.S. Financial inclusion of vulnerable sectors with a gender perspective: risk analysis model with artificial intelligence based on complex thinking // Journal of Innovation and Entrepreneurship. 2025. Vol. 14. No. 1. P. 4.
5. Pattnaik D., Ray S., Raman R. Applications of artificial intelligence and machine learning in the financial services industry: A bibliometric review // Heliyon. 2024. Vol. 10. No. 1.
6. Abdullah A.A.H., Almaqtari F.A. The impact of artificial intelligence and Industry 4.0 on transforming accounting and auditing practices // Journal of Open Innovation: Technology, Market, and Complexity. 2024. Vol. 10. No. 1. P. 100218.
7. Gera R., Chadha P., Saxena A., Dixit S.A scientometric and bibliometric review of impacts and application of artificial intelligence and fintech for financial inclusion // Artificial Intelligence, Fintech, and Financial Inclusion. CRC Press. 2023. P. 82-111.
8. Borodin I. The impact of integrated management information systems on cost control efficiency in large construction and engineering projects // International Journal of Latest Engineering and Management Research. 2025. Vol. 10(03). P. 24-27.

9.   Elliott K., Price R., Shaw P., Spiliotopoulos T., Coopamootoo K., Van Moorsel A. Towards an equitable digital society: artificial intelligence (AI) and corporate digital responsibility (CDR) // Society. 2021. Vol. 58. No. 3. P. 179-188.

10.   Mahalakshmi V., Kulkarni N., Kumar K.P., Kumar K.S., Sree D.N., Durga S. The role of implementing artificial intelligence and machine learning technologies in the financial services industry for creating competitive intelligence // Materials Today: Proceedings. 2022. Vol. 56. P. 2252-2255.