INTERNATIONAL JOURNAL OF EUROPEAN RESEARCH OUTPUT
ISSN: 2053-3578 I.F. 12.34

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APPLICATION OF ARTIFICIAL INTELLIGENCE METHODS IN THE BANK RISK MANAGEMENT SYSTEM

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Abstract. This article analyzes the main factors affecting the financial efficiency and return on capital of commercial banks based on an econometric approach and substantiates the prospects for the use of artificial intelligence technologies in improving the bank's risk management system. The study took ROE as the outcome indicator, and the impact of the volume of digital banking operations, the country's GDP, the number of users of digital services, and the level of problem loans on it was estimated using a multifactor logarithmic regression model. The empirical results confirmed that digitalization processes and macroeconomic growth have a positive effect on bank profitability, while problem loans have a negative effect. Model diagnostics showed a normal distribution of balances, ensuring statistical reliability of the assessments. It also highlighted the advantages of artificial intelligence methods based on machine learning, neural networks, and "big data" analysis in reducing credit risks, early detection of the probability of default, and increasing operational efficiency. The results of the study show that the introduction of innovative risk management mechanisms in banks enhances financial stability and competitiveness.

Keywords: financial stability, commercial banking, risk management in banks, risk management, artificial intelligence methods.

1.Introduction

Commercial banks face various and multifaceted risks in their daily financial and economic activities. Each type of banking risk differs in terms of its source of occurrence, the scale of the potential threat to financial stability, and the consequences it poses for the bank if the risk materializes. It is worth noting that one of the main trends in banking in the current decade is the introduction of intelligent systems to improve existing risk management. This is explained, first of all, by the rapid development of artificial intelligence and its active penetration into all business processes of the bank. On the one hand, in the current conditions, the introduction of modern intelligent technologies is becoming an important competitive advantage in the activities of commercial banks. However, on the other hand, this process is also causing the emergence of new types of threats associated with the introduction of artificial intelligence systems. While modern technologies have significantly simplified many routine business processes and allowed commercial banks to focus on strategic tasks, even the most advanced artificial intelligence systems remain vulnerable to operational risks. Therefore, financial institutions are required to be cautious and careful when using innovative technologies.

2.Literature review

The issues of credit risk management and the use of artificial intelligence technologies in commercial banks are widely covered in scientific literature as one of the important areas of the modern concept of financial security. Golubova et al. (2023) consider credit risks within the framework of the concept of economic security and substantiate that bank stability is inextricably linked to asset quality, diversification, and internal control systems. Dyakov et al. (2021) interpret credit portfolio monitoring, the use of scoring models, and mechanisms for early risk identification as the main instruments of effective management. In recent years, the introduction of digital technologies into risk management processes has become particularly important. Mikhaylov (2023) evaluates artificial intelligence as a tool that increases forecasting accuracy and reduces errors due to the human factor, emphasizing the need to integrate it into complex risk analytics platforms. Kashavorova and Panova (2020) provide empirical evidence that AI can improve efficiency in lending, antifraud, and customer segmentation in the transformation of the financial ecosystem. Algorithmic models also have an advantage in investment decision-making, and Sviridov (2024) notes their speed and big data processing capabilities as promising areas, but information security and ethical risks as limiting factors. Semeko (2021), who analyzed institutional problems in the banking sector, emphasizes the importance of human resources and regulatory compliance in technological implementation, while Gorodetskaya and Gobareva (2022) consider the main trends in AI application - automated scoring, robo-analytics, and real-time monitoring - as factors that increase the competitiveness of banks. In general, the reviewed studies confirm that the integration of digital solutions based on artificial intelligence, along with traditional financial instruments, in credit risk management is the methodological basis for ensuring the stability and economic security of banks (Golubova et al., 2023; Dyakov et al., 2021; Mikhaylov, 2023; Kashovarova & Panova, 2020; Sviridov, 2024; Semeko, 2021; Gorodetskaya & Gobareva, 2022).

3.Analysis and results

Before analyzing the main trends in the use of artificial intelligence methods and tools in modern banking, it is necessary to clarify such a multifaceted concept as “risk”. In the professional literature, the term “risk” is given different definitions depending on its scope and research direction. However, in the context of banking management, risk is understood as a potential threat that arises in the business processes of a bank and can undermine its financial and reputational stability.

In order for a commercial bank to correctly identify and forecast the likelihood of risky events, banking risks are divided into the following types in the professional literature: credit risks, operational risks, market risks, legal risks, political (country) risks and liquidity risks [1]. In the framework of this article, it is precisely the risk groups in which artificial intelligence technologies are actively used - credit, market, operational and liquidity risks - that will be considered and analyzed.

Among the risks that have the greatest impact on the financial results and stability of a commercial bank are credit risks. In response to the emergence of credit risks, financial institutions develop and regularly improve credit policies aimed at reducing the probability of default. This aspect is especially relevant in times of economic instability, since in the current conditions, credit errors made by banks of particular systemic importance can negatively affect the financial stability of the entire banking system of the country.

Every year, the number of factors that must be taken into account to accurately assess the borrower's credit rating is increasing. These factors include not only financial indicators, such as income level, but also many non-financial factors. In particular, indicators such as the client's business reputation, the presence of late payments, the borrower's family composition, the number of children, the structure of transactions on bank accounts significantly complicate the credit assessment process. It has become practically impossible for bank employees to analyze these numerous parameters qualitatively and quickly.[2] As a result, without the introduction of artificial intelligence systems, the response time to loan applications would have been significantly longer, and the quality of the assessment would not have been high enough.[3]

That is why modern banks are increasingly actively introducing various tools based on artificial intelligence to assess the borrower's credit rating. Nowadays, modern banking is unthinkable without these technologies. One of the most important artificial intelligence tools in credit scoring is the clustering of the customer base and the automation of decision-making processes for granting loans. Today, there are many intelligent systems that allow banks to respond to the issue of a loan or refuse it within minutes. These artificial intelligence systems evaluate the borrower based on hundreds of indicators, identify unusual relationships in large volumes of data, and thereby minimize the likelihood of default.

Examples of such AI solutions being implemented in credit scoring include the Upstart and OnDeck Capital platforms. While Upstart's intelligent system automates the daily processes of analyzing consumer loan applications and making decisions, OnDeck Capital's platform effectively assists banks in the process of granting loans to small businesses.

Another AI tool that banks should implement to improve the process of controlling credit risks is stress testing of the loan portfolio. While banks can independently model the stability of the loan portfolio in relation to changes in the unemployment rate, interest rates or inflation, the use of AI systems allows them to model various scenarios of deviations in real time. With the help of intelligent systems, banks can have quick and accurate information about the potential impact of any macroeconomic changes in the country on the share of defaults in their loan portfolio.

Artificial intelligence systems based on deep learning are capable of simulating hundreds of scenarios at once, giving banks a broader picture of the threats and their impact on banking operations [4]. The use of artificial intelligence tools in stress testing a loan portfolio gives banks important signals about what level of unemployment or inflation indicators may be a critical threshold for mass defaults on loans. It is almost impossible to perform such a detailed and accurate analysis manually. Among the artificial intelligence-based solutions for assessing the stability of loan portfolios, the Moody's Analytics and S&P Global Market Intelligence platforms stand out.

ROE (Return on Equity) is a key financial indicator that shows the efficiency of a bank's use of its own capital, and expresses how much income (net profit) the funds invested by the bank's shareholders bring.

Table 1

Analysis of factors affecting the efficiency of using equity capital of commercial banks

LnROE	lnDig_bank_oper	LnGDP	LnDig_user_serv	lnNPL
Efficiency of use of equity capital	Digital banking operations	Country GDP	Number of people using digital technologies	Volume of problem loans in

ISSN: 2053-3578 I.F. 12.34

of commercial banks	in commercial banks			commercial banks

In this econometric study, the impact of the main macroeconomic and digital transformation factors affecting the return on equity (ROE) of commercial banks was assessed based on a multivariate logarithmic regression model. The model adopted LnROE as the outcome indicator, and included the volume of digital banking operations in commercial banks (LnDig_bank_oper), the country's gross domestic product (LnGDP), the number of digital technology users (LnDig_user_serv), and the volume of non-performing loans (LnNPL) as explanatory factors. The economic interpretation of the model parameters in the log-log form is expressed through elasticity coefficients, that is, a 1 percent change in the factors reflects the percentage change in the outcome indicator. According to the calculation results, the coefficient of determination of the model is $R^2 = 0.967$, which indicates that about 96.7 percent of the changes in ROE are explained by the selected factors. The high value of the F-statistic and its probability close to zero confirm that the model is statistically significant in general, which indicates the practical and scientific reliability of the constructed regression equation.

Table 2

Regression analysis of factors affecting the efficiency of using equity capital of commercial banks

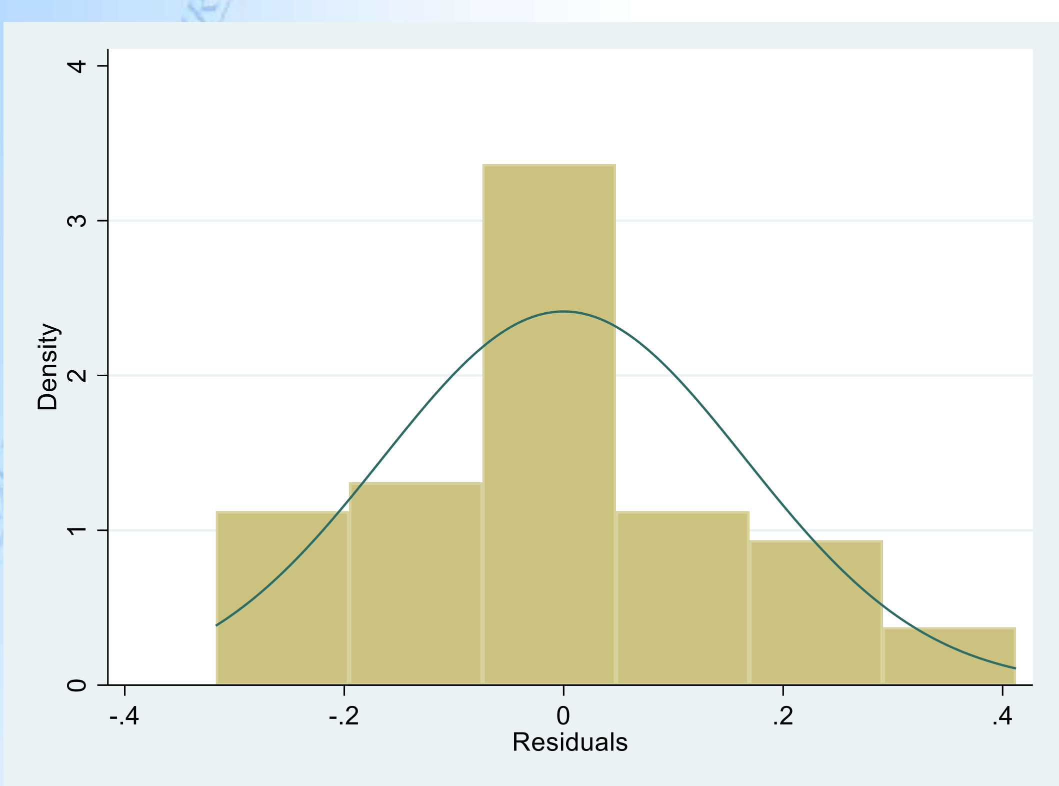
Source	SS	df	MS
Model	34.5729123	4	8.64322807
Residual	1.1747443	39	.030121649
Total	35.7476566	43	.83134085

Number of obs	=	44
F(4, 39)	=	286.94
Prob > F	=	0.0000
R-squared	=	0.9671
Adj R-squared	=	0.9638
Root MSE	=	.17356

lnroe	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
lndig_bank_~r	1.910402	.8517541	2.24	0.031	.1875667	3.633237
lngdp	1.752806	.1132627	15.48	0.000	1.523711	1.981902
lndig_user_~v	1.50105	.3566215	4.21	0.000	.7797149	2.222385
lnnpl	-.861488	.2826492	-3.05	0.004	-1.4332	-.2897761
_cons	-16.25487	3.529928	-4.60	0.000	-23.39482	-9.114915

LnROE=−16.25+1.91LnDig_bank_oper+1.75LnGDP+1.50LnDig_user_serv−0.86LnNPL

The results show that the increase in the volume of digital banking operations has a significant positive impact on ROE: respectively, the coefficient is positive and greater than unity, indicating that digitalization processes in banking are increasing the return on capital by reducing costs, increasing transaction speed and enhancing service efficiency. Similarly, the growth of the country's GDP has a strong multiplicative effect on the profitability of banks, while macroeconomic stability, business activity and the expansion of lending volumes contribute to improving financial results. The increase in the number of users of digital services also has a positive elasticity, which means that the expansion of the customer base through remote banking services, mobile applications and fintech platforms increases banks' non-interest income and operational efficiency. Conversely, an increase in the volume of problem loans was found to have a negative impact on ROE, since poor-quality assets in the loan portfolio increase the need for provisioning, reduce profit margins and limit the effective use of capital.



The graph shows that the residuals are concentrated around zero, with most of them concentrated between −0.2 and +0.2. The distribution is close to symmetrical, with the peak located in the center and gradually decreasing to both sides. This indicates that the residuals are approximately normally distributed. The coincidence of the histogram bars with the normal curve indicates that there are no systematic deviations or strong asymmetry in the model. Therefore, it can be assumed that the coefficients estimated in the regression results are reliable and the statistical tests (t-test, F-test) were used correctly.

Also, there are almost no sharp “tails” or extreme outliers in the distribution. This means that there are no large errors or misspecification in the model, and there are few sharply different observations in the data. The location of the residuals in a relatively narrow interval is also consistent with the low Root MSE value and indicates high forecasting accuracy. This result confirms that the selected factors - digital transactions, GDP, digital service users, and non-performing loans - are sufficiently important in explaining bank profitability (ROE).

Table 3

Correlation analysis of factors affecting the efficiency of using equity capital of commercial banks

	lnroe	lndig_~r	lngdp	lndig_~v	lnnpl
lnroe	1.0000				
lndig_bank~r	-0.7021	1.0000			
lngdp	0.9625	-0.8226	1.0000		
lndig_user~v	-0.0483	0.5817	-0.2274	1.0000	
lnnpl	0.4068	0.1534	0.2891	0.7994	1.0000

However, the graph may show a very small positive skewness, which means that in some periods the ROE forecast is slightly higher than the actual value. However, this skewness does not pose a significant statistical problem. However, from a scientific point of view, it is recommended to additionally formally check normality using the Jarque–Bera or Shapiro–Wilk tests.

Skewness and kurtosis tests for normality

Variable	Obs	Pr(skewness)	Pr(kurtosis)	Joint test Adj chi2(2)	Joint test Prob>chi2
ehat	44	0.5913	0.9633	0.29	0.8649

```
. hist ehat, norm
(bin=6, start=-.3170346, width=.12154896)
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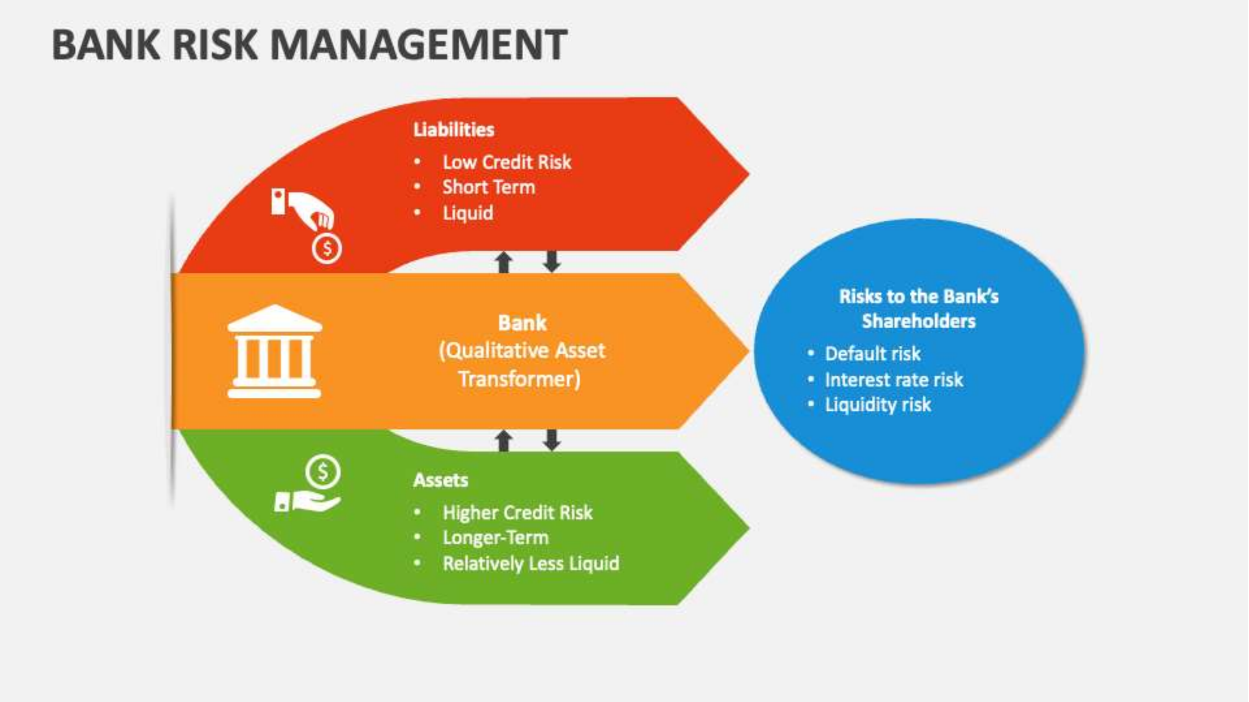
In general, the distribution of residuals shows that the regression model meets the conditions of the classical MLR, the estimates are unbiased and efficient, and the model can be used for scientific research and forecasting purposes. This confirms the methodologically correct choice of the econometric model developed within the framework of the dissertation and the high reliability of the empirical results.

The results obtained scientifically confirm that digital transformation and macroeconomic growth are decisive factors in increasing the efficiency of commercial banks, and credit risk management is a key condition for stability. Therefore, expanding the digital ecosystem in the banking system, increasing the share of online services, introducing risk management mechanisms based on artificial intelligence and data analysis, and strengthening strategies for reducing problem loans are recommended as priority areas for sustainably increasing ROE. This regression model serves as an important analytical tool for forecasting the activities of commercial banks and making strategic decisions.

The next important group of risks actively managed by banks using intelligent systems is market risks. They, like credit risks, are one of the main types of risk in the bank's risk management system. This group of risks is primarily associated with fluctuations in the value of bank assets and liabilities as a result of changes in market conditions, including changes in interest rates, exchange rates, and the value of securities.

Market risk is multifactorial, and each factor plays an important role in ensuring the financial stability of the bank. For example, the realization of interest rate risk can significantly reduce the profitability of a commercial bank on loans to borrowers. This is due to an increase in the cost of resources attracted to maintain liquidity, which ultimately reduces the overall profitability of the financial institution. Currency risk is explained by high fluctuations in foreign exchange rates. This situation can significantly increase the costs of attracting liquidity in foreign currency, as well as lead to an increase in real interest payments on funds attracted by the bank abroad.

In times of economic instability, a fraction of a second in concluding a transaction in financial markets can be crucial. Therefore, such artificial intelligence systems allow a bank to significantly reduce the likelihood of market risks, since time delays in executing transactions can lead to multi-million dollar financial losses.[5]



Another relevant tool based on artificial intelligence and being introduced into the bank's risk management system are intelligent risk hedging systems. These algorithms are used to develop a bank's market risk hedging strategies and serve to protect a commercial bank from unexpected adverse market fluctuations. The tasks solved by such systems include making decisions on the purchase or sale of derivative financial instruments - in particular, options and futures - depending on the forecasted changes in market conditions.

To manage liquidity risk, modern banks are increasingly using various instruments based on artificial intelligence. One of these instruments is stress test modeling. The essence of this method is that with the help of SI systems, banks have the opportunity to process large volumes of data in real time, which is practically impossible with manual processing in large commercial banks. Modern SI instruments allow you to automate stress modeling processes and free up qualified employees for other important strategic tasks.

As part of stress testing with the help of artificial intelligence, commercial banks can solve a number of important tasks. In particular, it is possible to forecast scenarios such as a sharp outflow of deposits, changes in interest rates, the introduction of sanctions against the financial system and assess their impact on bank liquidity. Such stress modeling capabilities are provided by advanced SI instruments based on deep learning algorithms such as TensorFlow and PyTorch. These technologies allow for rapid forecasting of changes in bank liquidity, taking into account customer behavior or changes in market conditions.[7]

Another important area of application of artificial intelligence in liquidity risk management is monitoring of market conditions and information (news) context. With the introduction of SI-systems, banks will be able to quickly receive changes in market conditions or news that can significantly affect the level of liquidity in real time. The speed of such monitoring is tens, even hundreds of times higher than traditional information monitoring carried out by an employee.

Using natural language processing (NLP) algorithms, SI-systems quickly identify negative information related to market changes in the Internet space and automatically classify news according to their significance and potential impact on the stability of the bank. Since NLP tools allow for the analysis of the context of news and messages, systems can quickly classify incoming information into positive and negative categories. This allows banks to adapt their operations much more quickly to changing economic conditions.

The results of the above econometric analyses clearly demonstrate that the financial stability and return on capital of commercial banks largely depend on the level of credit risk and digital transformation indicators. In particular, according to the results of the regression model, it was found that an increase in the volume of problem loans (NPL) has a negative impact on ROE and reduces the financial efficiency of banks, while, on the contrary, an increase in the level of digital transactions and the use of digital services by customers significantly increases profitability. The closeness of the distribution of residuals to the normal form confirms the statistical reliability of the model and the empirical validity of the identified relationships. These results indicate the need to further improve risk management processes in banking. From this point of view, the use of artificial intelligence (AI) methods in the banking risk management system is of strategic importance. Unlike traditional assessment mechanisms, AI technologies allow for real-time processing of large volumes of data, identification of hidden patterns, and advance forecasting of credit risks. In particular, machine learning algorithms help reduce NPL levels by automating credit scoring, accurately assessing customer solvency, and identifying the likelihood of default at an early stage. Neural networks and big data analysis also serve as effective tools for detecting fraudulent transactions, monitoring liquidity risks, and optimizing portfolio diversification.

As a result, a risk management system based on artificial intelligence reduces operating costs, increases decision-making speed, and reduces errors related to the human factor. This increases the efficiency of bank capital use and strengthens financial stability. Therefore, the introduction of SI technologies in commercial banks should be considered not only as a factor of innovative development, but also as an important institutional mechanism for reducing credit risks and sustainably increasing ROE indicators.

Summarizing the results of the study, a number of important aspects can be highlighted. First of all, in modern economic conditions, commercial banks are faced with more and more types of risks in their daily activities. This situation increases the need to form an effective risk management system in order to ensure financial stability and competitiveness. Traditional risk management methods are becoming increasingly inadequate due to the transformation of the conditions of financial market activity. Therefore, banks have become leading subjects of digital business transformation and are introducing dozens of new solutions and systems based on artificial intelligence.

Today, artificial intelligence technologies and methods are becoming an indispensable condition for ensuring the competitiveness and efficiency of commercial banks. Because they allow financial organizations to analyze large volumes of data in a short time, identify hidden negative patterns that can undermine financial stability and reduce the profitability of the organization.

The risk groups in which artificial intelligence is most actively used today include credit risks, market risks, operational risks, and liquidity risks. The number of instruments on the market aimed at effectively managing these types of risks is increasing from year to year. They can partially or completely replace the work of hundreds of qualified employees, automate routine processes and allow human resources to be directed to solving the most important strategic tasks.

At the same time, it should be noted that the introduction of intelligent systems is not an absolute advantage for banks. Because this process also creates the possibility of the emergence of new types of risks associated with corporate data leakage, technical failures or errors in algorithmic systems.

In conclusion, the integration of artificial intelligence into the risk management system of commercial banks is an important stage on the path to digital transformation and development of the financial sector. This process strengthens the stability of financial organizations, increases the efficiency and profitability of business activities. In the future, further development of machine learning technologies and their introduction into more and more business processes of the bank are expected, which will allow financial organizations to manage emerging new and uncertain risks faster and more effectively.

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