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Forecasting bank cash flows using intelligent systems

Abstract. The object of the study is the processes of cash flow management in the banking system of Ukraine, which is characterized by high dynamism, increased risks caused by war and economic instability, as well as rapid adaptation to digital technologies and European standards. The article emphasizes the critical importance of effective cash flow management to maintain financial stability and ensure uninterrupted operations of the bank in the face of uncertainty.

Problem statement. The main problem studied in the article is the lack of efficiency of traditional methods of forecasting and managing cash flows in modern realities. These methods are unable to adequately process large amounts of data, take into account complex nonlinear dependencies, and respond quickly to unpredictable changes caused by both war and digital transformation. This creates liquidity risks, leads to suboptimal use of capital, and reduces the overall resilience of the banking system.

Unresolved aspects of the problem. Today, there are gaps in the integration of the latest intelligent systems directly into the bank's operational and strategic processes. There are still unanswered questions about how to turn highly accurate predictions obtained through machine learning into concrete, managerial decisions that will minimize risks.

Purpose of the article. The aim of the article is to develop comprehensive recommendations for improving cash flow management in a bank using intelligent systems. For this purpose, a three-dimensional approach is used, which combines Big Data analysis, improving the accuracy of forecasts using machine learning, and their integration into a management decision support system.

Presentation of the main material. The authors of the article use a three-dimensional coordinate system of "analysis-prediction-integration" to structure the research. Practical examples for forecasting liquidity, assessing borrowers' solvency, and the effectiveness of marketing campaigns are considered. The use of LSTM, SVM, Random Forest, and RNN models to improve forecasting accuracy is detailed. To integrate the forecasting results into the bank's risk management system, specific solutions are proposed, such as the use of automated dashboards, early warning systems, and dynamic scoring.

Conclusions. The recommendations proposed in this article allow banks to move from reactive to proactive cash flow management. This helps to significantly reduce operational risks, optimize capital, increase profitability and strengthen competitive positions. The practical value of the study lies in the provision of specific tools and scenarios for the implementation of intelligent systems in daily operations, which is extremely important for ensuring the financial stability of the Ukrainian banking system in the face of uncertainty.

Keywords: *risk, integration, machine learning, liquidity, financial stability of the bank, risk management system of the bank.*

Formulas: –; fig.: 3; tabl.: 3; bibl.: 12.
JEL Classification G21, D81, L86, R51.

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Introduction. The issue of improving the efficiency of cash flow management in the bank's risk management system is extremely relevant for Ukraine, especially given the current realities: constant risks due to the war, at the same time as the rapid development of digital banking technologies and compliance with EU conditions for the functioning of the banking system.

The war causes significant economic instability, which directly affects banks' cash flows. Unpredictable events, changes in consumer and investment behavior, and infrastructure destruction pose huge challenges for liquidity forecasting and management. Banks need to have reliable mechanisms to quickly adapt to changing conditions. At the same time, there is a growing risk that the bank will not be able to meet its obligations due to deposit outflows or lack of external funding. Effective cash flow management is key to preventing liquidity crises and maintaining financial stability. The digitalization of banking (online banking, mobile applications, instant payments) significantly accelerates the movement of funds and changes traditional cash flow models. This requires banks to review and modernize their existing forecasting and management systems.

Cash flow forecasting using intelligent systems is particularly relevant. The large amounts of data generated by digital transactions can only be efficiently processed using machine learning and artificial intelligence algorithms. This will allow banks to make more accurate forecasts, identify hidden patterns, and respond quickly to changes.

At the same time, the development of digital technologies also creates new risks associated with cybercrime and system failures. Cash flow management should take these risks into account by integrating security measures and contingency plans.

To create a holistic and effective bank cash flow management system, three components are important, which are complementary and critical: forecasting the bank's cash flows provides a basis for decision-making; developing scenarios for managing the bank's cash flows allows preparing for different scenarios, which is especially important in an environment of uncertainty; formulating recommendations for choosing a cash flow management strategy provides practical tools for making informed management decisions.

The basic component of the bank's cash flow management system is cash flow forecasting based on intelligent systems, as cash flow management in a modern bank, especially in the digital economy, requires not only an understanding of past trends but also accurate forecasting of the future.

Literature review. A review of scientific papers on the topic under consideration allows us to identify key approaches to its study.

Classical works on liquidity and cash flow management, such as those by Allen E. Bukhari and his colleagues [5], focused on models that used time series analysis methods to forecast cash flows. The main idea of these approaches was to extrapolate past trends to the future. However, classical methods do not take into account nonlinear dependencies, which makes them ineffective in financial crises. The limitations of traditional methods are particularly evident in the digital economy, when the volume and speed of data generation require more sophisticated tools.

With the advent of Big Data technologies and the development of computing power, scientific thought has begun to shift toward intelligent systems. Michael Nolan [9] emphasizes in his study that Big Data provides banks with the opportunity to analyze not only traditional financial indicators, but also huge amounts of unstructured data (customer behavior in social networks, geographic data, real-time transaction information). This allows them to get a more complete picture of the client's financial situation and market trends.

The works of researchers such as Robert Shlepachuk [11], Weixi Chen, Walayat Hussain, and others [6] demonstrate the effectiveness of machine learning for cash flow forecasting. They showed that neural networks significantly outperform classical models in forecasting accuracy, especially for short-term periods. This is due to their ability to detect complex, hidden patterns in large amounts of data that are nonlinear and volatile.

Thus, scientific thought has evolved from classical econometric models to complex intelligent systems. The work of these and other researchers is becoming the basis for the development of more complex hybrid models that combine different machine learning algorithms, as well as on the ethical use of AI and cybersecurity in the context of cash flow management.

Purpose, objectives and research methods. Traditional forecasting methods often fail to cope with the complexity and volume of data generated by digital banking operations. That's why intelligent systems based on Big Data and machine learning are becoming an indispensable tool for improving the accuracy and efficiency of cash flow forecasting. This allows the bank not only to optimize its liquidity but also to effectively manage the risks associated with cash flows.

The purpose of the study is to develop and substantiate comprehensive recommendations for improving the efficiency of cash flow management in the bank's risk management system in the context of economic instability caused by the war and rapid digital transformation. The study aims to demonstrate how the integration of intelligent systems based on Big Data and machine learning can transform traditional approaches to forecasting and managing financial flows, turning them into a proactive tool for reducing risks and optimizing a bank's operations.

To achieve this goal, the study set and solved the following tasks: analyzed the possibilities and advantages of using Big Data technologies and analytical tools for analyzing and forecasting cash flows; identified key machine learning models that can be used to improve the accuracy of cash flow forecasts; developed practical scenarios and recommendations for integrating forecasting results into the bank's management decision support system.

The study uses a set of general scientific and special methods, such as the method of system analysis and synthesis to form a holistic concept of cash flow management; the method of analysis and generalization to study the experience of using intelligent systems in the banking sector; the method of scenario planning to develop practical recommendations in the format of "Task - Decision - Result" chains, which allows preparing for different scenarios and the method of data visualization to present key conclusions.

Research results. To develop recommendations for improving the methods of analyzing and forecasting the bank's cash flows, we will apply a three-dimensional approach based on the construction of a coordinate system (Fig. 1), in which we consider the following axes: A (analysis) - the state of analysis and forecasting of cash flows using Big Data and analytical tools; FA (forecast accuracy) - the state of accuracy of cash flow forecasting, I (integration) - integration of cash flow forecasting into the bank's decision support system.

Each R (recommendation) for improving the methods of analysis and forecasting of the bank's cash flows will depend on the current state of IS use in the three areas indicated - $R_t\,(A_t\,, FA_t\,, I_t\,)$.

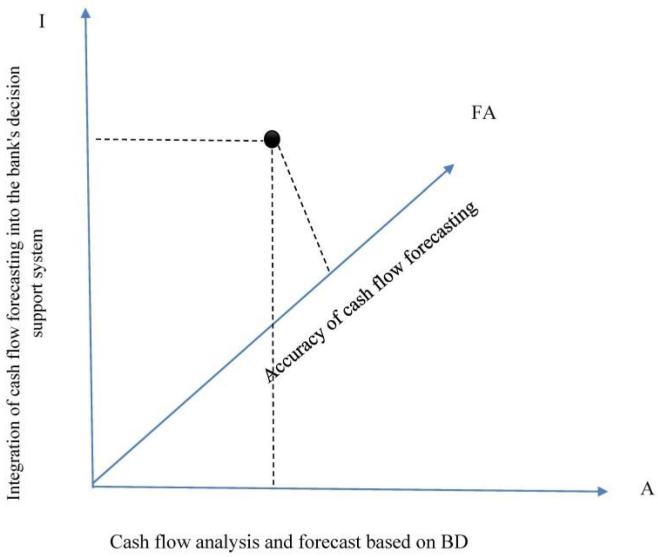

Figure 1. Coordinate system for forecasting bank cash flows based on intelligent systems
Source: prepared by the authors

Discussion.

Let's take a closer look at Axis A, i.e., the possibilities of improving cash flow analysis and forecasting using Big Data and analytical tools. Large volumes of data generated by banking activities can be used to obtain valuable analytical data and make accurate forecasts.

The conceptual scheme of applying Big Data and analytical tools for analyzing and forecasting cash flow is shown in Figure 2.

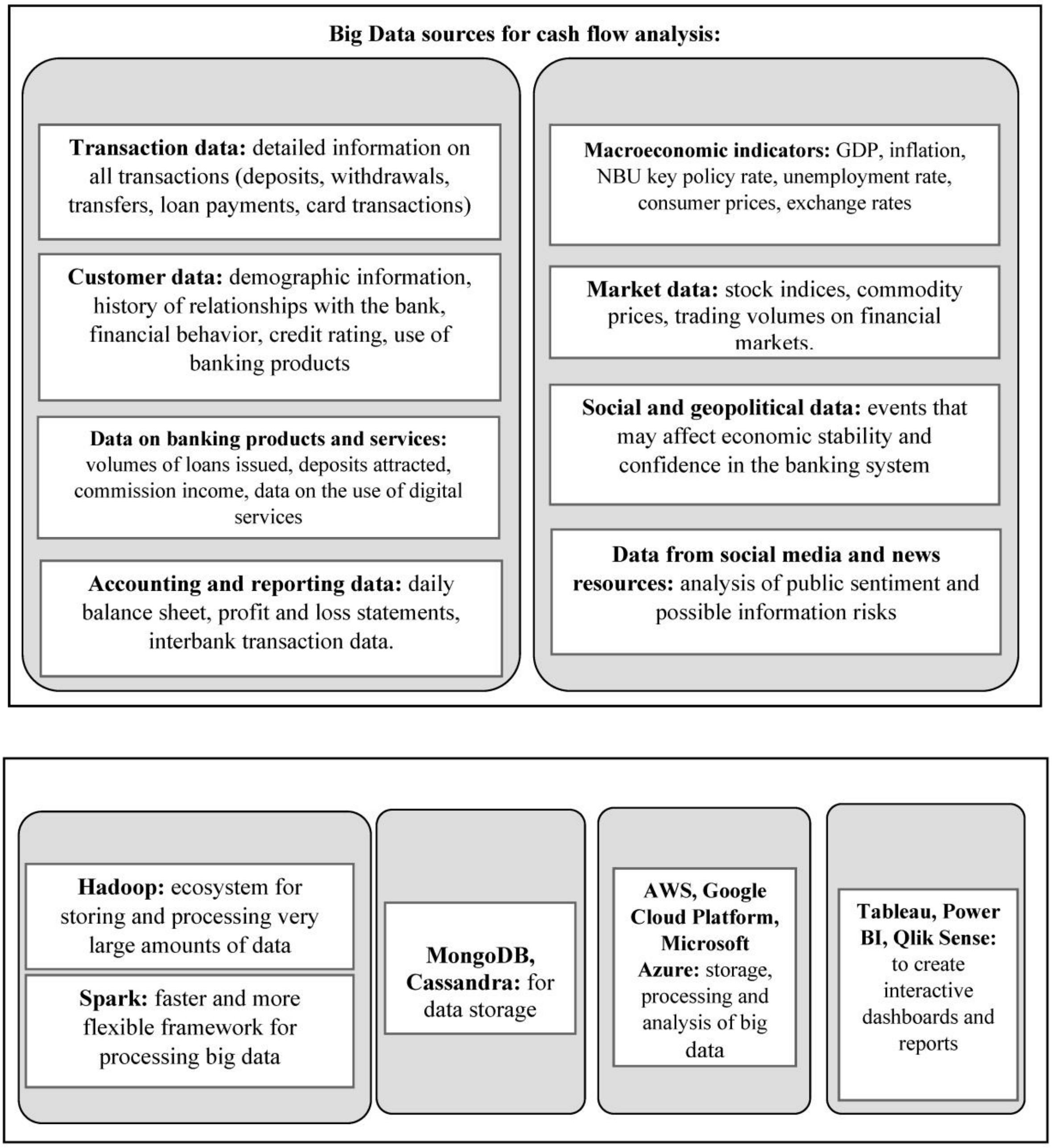

Figure 2. Scheme for applying Big Data and analytical tools to analyse and forecast cash flows.
Source: prepared by the authors

Table 1. A chain of recommendations: 'Task' > 'Relevance' > 'Solution' > 'Result', regarding the application of Big Data and analytical tools for cash flow forecasting

Bank's objectives	Relevance	Solutions using Big Data and analytics		Expected result
		Data sources	Tools	
Daily liquidity forecasting and cash management	The need to accurately forecast daily cash inflows and outflows, customer account balances	**Internal:** Historical data of all transactions (withdrawals, deposits, transfers, payments) broken down by time, client type, transaction type, and geography. Data on salaries, pensions, and social benefits. Data on loan debt and repayment schedules. **External:** Calendar data (holidays, weekends, payment days), weather conditions (affecting branch attendance), macroeconomic indicators, data on competitors' activities.	**Collection and storage:** Apache Kafka (real-time transactional data transfer), Hadoop Distributed File System (HDFS), or cloud storage (storage of huge amounts of data). **Processing:** Apache Spark for fast data processing and aggregation, feature extraction. **Modeling:** LSTM (Long Short-Term Memory) or GRU (Gated Recurrent Unit) - neural networks for forecasting daily cash flows, GBoost/LightGBM for identifying key factors affecting cash outflows/inflows	Highly accurate forecasts of cash requirements and expected account balances, which allows optimizing collection routes, reducing cash logistics costs, and minimizing funds that are "frozen" in the form of excess reserves. The forecast accuracy can increase by 15-20% compared to traditional methods.
Assessment and forecasting of borrowers' solvency (default forecast)	The need to take into account dynamic changes in the client's financial condition, which will increase the accuracy of default forecasts	**Internal:** Data on customer transactions (regularity of income/expenses, balance dynamics), frequency of use of banking products, loan repayment history, overdrafts, data from the suspicious transaction monitoring system. **External:** Data from credit bureaus, public data on court decisions, tax arrears (for legal entities), macroeconomic indicators (changes in unemployment rates in the borrower's industry), data from social networks.	**Collection and storage:** Apache Flink (real-time data stream analysis). Data Lake (consolidation of heterogeneous data). **Processing:** Spark Streaming, Python with Pandas and NumPy libraries (data preparation) **Modeling:** Random Forest, Gradient Boosting (binary classification (default/non-default, effective processing of a large number of heterogeneous features). Deep neural networks (detection of complex hidden patterns in customer financial behavior that may indicate increased risk).	Dynamic assessment of default risk for each borrower. Subsequent interaction with customers showing early signs of financial difficulties (loan restructuring, reduction of monthly payments), reducing the level of problem debt and optimizing the formation of reserves. The accuracy of default forecasts can increase by 10-25%.
Forecasting demand for banking products and the effectiveness of marketing campaigns	The need to identify products that will be in demand in the future and optimize marketing budgets	**Internal:** Customer purchase history, interaction with mobile apps/online banking, calls to the call center, demographic data, transaction history. **External:** Socio-demographic data by region, competitor data, news about changes in legislation affecting the banking market, trends in social media and internet search.	**Collection and storage:** Google BigQuery or Snowflake (integration of structured and unstructured data from various sources). **Processing:** Apache Hive or Presto (execution of complex queries and data aggregation). **Modeling:** collaborative filtering or deep learning-based recommendation systems (personalized product recommendations). Regression models (forecasting demand for specific products). **Clustering using K-Means or DBSCAN methods** (segmenting customers based on their behavior and needs).	Reliable forecasts, demand for products in specific customer segments, personalization of marketing offers. As a result, increased campaign conversion, reduced marketing costs, and optimized cash flow from product sales.

Source: prepared by the authors based on [2, 4, 12]

Given that detailed internal data of specific banks is confidential, this section of the study will provide generalized examples of real banking tasks and recommendations or scenarios for solving them in the form of a specific "task-solution-result" chain. Let us form a chain: 'Bank task' - 'Relevance' - 'Solution' - 'Result' in order to formulate recommendations on the use of Big Data and analytical tools for forecasting cash flows in a bank (Table 1).

The table shows that the integration of Big Data and analytical tools allows banks not only to collect and store huge amounts of information, but also to transform it into valuable knowledge for accurate forecasting and effective cash flow management. This is the fundamental basis for building an effective risk management system in the digital economy.

Let us consider in more detail the FA axis, i.e., the direction of improving the accuracy of cash flow forecasting based on the use of machine learning models, the advantages of which are studied in detail in [11-12]. Let us present specific cash flow forecasting tasks in banks in the form of a chain 'Task' - 'Relevance' - 'Solution' - 'Result', and formulate recommendations on the use of machine learning models to improve the accuracy of the forecasts obtained (Table 2).

Table 2. Recommendation chain: 'Task' > 'Relevance' > 'Solution' > 'Result' for improving the accuracy of bank cash flow forecasts using machine learning models

Bank's task	Relevance of the task	Solution	Result
Optimizing liquidity management with LSTM, which can identify hidden risk factors	Accurate forecasts of daily cash flows are necessary to maintain optimal liquidity levels. Inaccurate forecasting can lead to excess reserves or cash shortages, which can cause liquidity risks and the need for expensive borrowing. Traditional econometric models often cannot handle the complex nonlinearities and long-term dependencies in daily transaction data.	Implementation of a long short-term memory (LSTM) model for forecasting daily cash inflows, taking into account data on transfer volumes, number of payments, customer salaries, loan maturity dates, as well as external factors such as macroeconomic indicators (GDP, inflation) and calendar events.	Increased forecasting accuracy, more accurate assessment of liquidity needs, optimization of capital allocation. Reduction of idle assets in reserves and minimization of short-term borrowing needs. The result is increased profitability and reduced operational risks.
Detecting anomalous cash flows to prevent fraud and money laundering using SVM and Random Forest (SVM can effectively recognize "normal" and "anomalous" features, while Random Forest helps identify which specific transaction features indicate a potential anomaly.	The constant threat of fraud and money laundering. The need to identify hidden anomalies in a huge volume of financial transactions.	Development of a monitoring system based on Support Vector Machines (SVM) for identifying anomalous transactions and Random Forest for classifying and determining factors affecting the anomaly. The basis for training models is transaction data (amounts, frequency, geography of operations, types of counterparties), as well as signs indicating fraudulent or suspicious operations.	Implementation of a system for automatic detection of potentially suspicious transactions that deviate from established customer behavior patterns, which will increase the effectiveness of financial monitoring and anti-fraud departments, allowing them to respond more quickly to threats, reduce financial losses, and ensure compliance with regulatory requirements.
Forecasting transaction volumes for infrastructure planning and customer experience management using recurrent neural networks (RNN) and gradient boosting (XGBoost). RNNs are effective for analyzing sequential data, while XGBoost effectively identifies complex relationships between various factors that affect cash flows.	The importance of forecasting future transaction volumes for effective planning of IT infrastructure, customer support resources, and network optimization. An inaccurate forecast can lead to system overloads, service delays, or, conversely, excessive investment.	Using RNN to analyze cash flow time series, taking into account their seasonality and cycles, as well as XGBoost to include additional factors (marketing campaigns, new product launches, macroeconomic events, holidays, and weekends).	Increased forecasting accuracy for future IT system planning, staffing allocation in contact centers and branches, and ATM cash optimization. The result is uninterrupted customer service, increased customer loyalty, and avoidance of unnecessary infrastructure costs.

Source: prepared by the authors based on [3,7,8]

Thus, using the specific banking tasks related to cash flow forecasting and analysis shown in the table as examples, we have examined the advantages of machine learning (nonlinear data processing, working with big data, adaptability) and specific models (LSTM, SVM, Random Forest, RNN, Gradient Boosting).

The success of cash flow forecasting depends not only on the accuracy of the models built, but also on the effectiveness of their integration into the bank's daily operations and strategic planning. This transforms forecast data into specific actions and management decisions. Let's take a closer look at axis I, i.e., the possibilities of integrating cash flow forecasting into the bank's decision support system, which shows how the developed models and obtained forecasts can be directly used in the bank's daily activities and strategic planning.

Possible directions for integrating cash flow forecasting into the bank's decision support system are grouped in Figure 3. The figure clearly shows how the results of Big Data analysis and machine learning can be directly applied in the practical activities of the bank. Figure 3 shows the interrelated areas: operational liquidity management, credit portfolio and default risk management, and strategic planning and new product development. Each area details specific scenarios, such as resource optimization, dynamic scoring, and customer behavior forecasting. The transition from simple forecasting to proactive management emphasizes that the effectiveness of intelligent systems depends not only on the accuracy of models, but also on their ability to be integrated into the bank's daily and strategic processes through tools such as dashboards and early warning systems.

Let us consider specific examples that reflect real scenarios of using forecasts in banking activities in the form of a chain: 'Task' - 'Relevance' - 'Decision' - 'Result', and formulate recommendations for integrating cash flow forecasting into the bank's decision support system (Table 3).

Table 3. A chain of recommendations regarding the integration of cash flow forecasting into the bank's activities: 'Task' – 'Relevance' – 'Solution' – 'Result'.

Task	Relevance	Solution	Result
Optimization of daily liquidity and cash management	Ensuring sufficient cash in branches and ATMs, as well as maintaining optimal liquidity levels for interbank settlements.	Automated liquidity dashboard; early warning system; automated recommendations; cash logistics optimization	Proactive work of the bank, reduction of operating costs, increased capital efficiency, minimization of liquidity risks, constant access for customers to the required amount of cash
Credit portfolio and default risk management	With a large credit portfolio, traditional creditworthiness assessment methods do not always accurately predict future defaults, leading to an increase in non-performing loans.	Dynamic scoring; risk segmentation; proactive actions; provisioning	Significant reduction in non-performing loans, improvement in credit portfolio quality, optimization of provisions, increased profitability
Strategic planning and development of new products	The need to develop new banking products and services that will meet the future needs of customers and ensure the bank's competitive position in the digital banking services market.	Forecasting customer behavior; identifying niches in the banking services market; developing innovative products; assessing the potential of new services	Launching innovative and in-demand products that meet market needs, increasing customer loyalty and ensuring a stable inflow of new cash flows, strengthening competitive positions in the banking system

Source: prepared by the authors based on [1,5,7-8]

Let's take a closer look at the solutions proposed to ensure the integration of cash flow forecasting into the bank's daily activities.

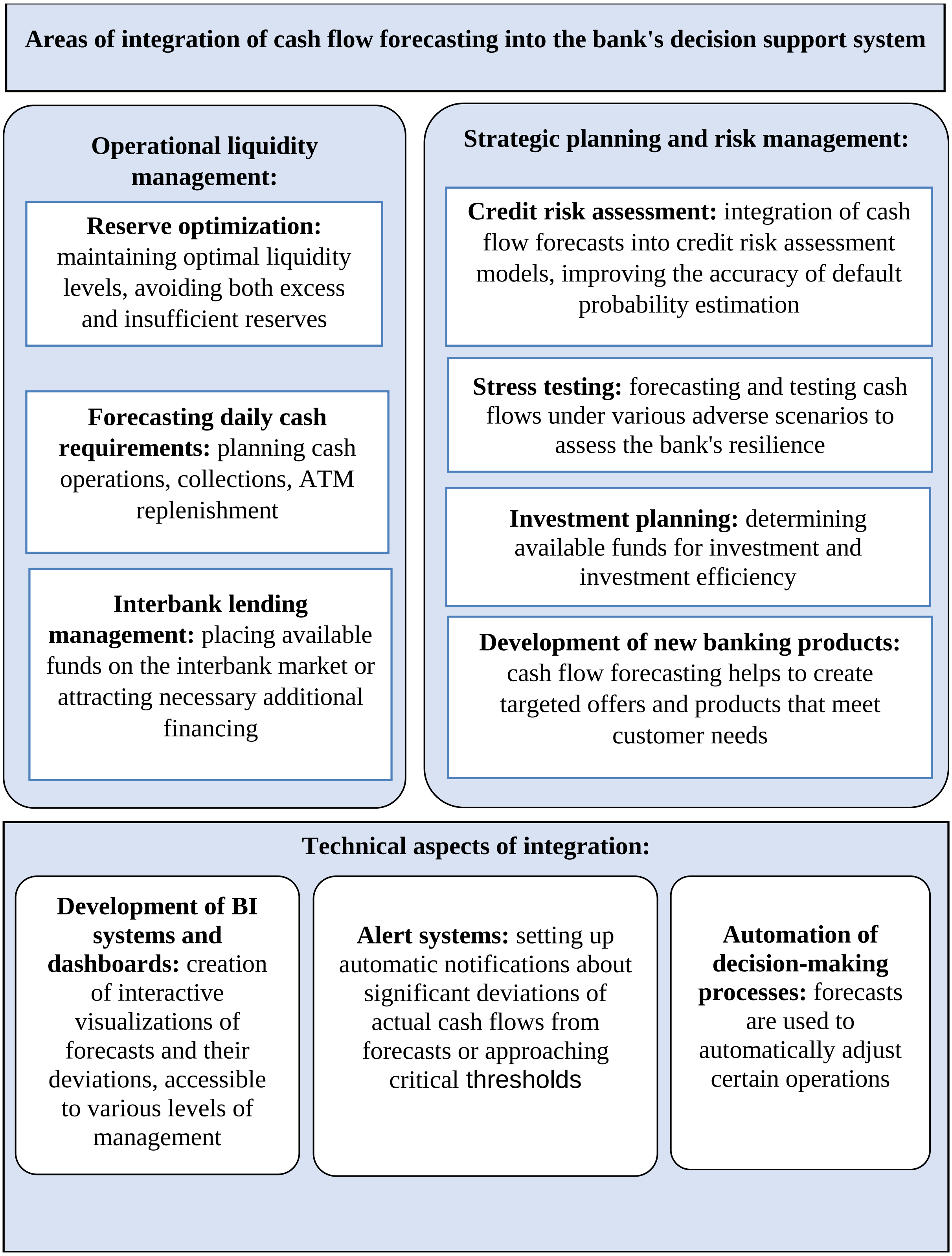

Figure 3. Directions for integrating cash flow forecasting into a bank's decision support system
Source: prepared by the authors

A dashboard is an information panel that displays key indicators that the owner of the tool or its users want to track. The purpose of creating a dashboard is to make a large amount of information understandable to a person. This is usually achieved through the visualization of dynamic data [10]. The development and implementation of an automated interactive bank liquidity dashboard involves the creation of a visual environment accessible to the treasury and management, which displays the following in real time:

- projected daily inflows and outflows of cash and non-cash funds;
- projected balances on correspondent accounts and in branch cash desks;
- critical liquidity thresholds;
- deviations of actual flows from projected ones in real time.

The development of an early warning system involves generating alerts (via SMS, email, or messages in the corporate system) for responsible bank employees in cases where the projected liquidity level approaches a critical mark or if actual outflows significantly exceed projections.

Setting up an automated recommendation system similarly involves generating specific measures (decisions) that will allow you to level out deviations in the current liquidity status from the forecasted one: reduce the amount of cash for collection in certain bank branches by a specific percentage, consider the possibility of placing excess funds on the interbank overnight market, prepare an application to attract additional liquidity on the interbank market in a certain amount, etc.

Cash logistics optimization involves the use of forecast data to optimize collection routes and schedules for replenishing/withdrawing cash from ATMs, which minimizes logistics costs and ensures uninterrupted customer access to cash.

The proposed solutions for credit portfolio and default risk management involve the use of dynamic scoring, i.e., continuous analysis of customer cash flows, taking into account forecasts obtained through machine learning. Also, in order to optimize the loan portfolio and reduce the risk of default, the bank segments borrowers according to the forecast values of their cash flows: if a significant decrease in income or an increase in irregular payments is forecast, the borrower is considered to have a high risk of default; if cash flows are stable, but there are external macroeconomic factors that may have a negative impact in the future, the risk is medium, and borrowers with stable and growing cash flows are considered low risk. With regard to segmented borrowers, the bank's proactive actions should be differentiated: the automated system should notify credit managers of the need to communicate with high-risk customers (offers of debt restructuring, credit holidays, consultations, etc.); for customers in the medium-risk segment – offers of loan insurance or financial advisory services to reduce risk; for customers in the low-risk segment – an individual approach to new banking products, increased limits, etc. In order to minimize credit risk in the event of default forecasts based on cash flow analysis, it is also advisable to obtain the necessary reserves for possible loan losses. This meets regulatory requirements and at the same time optimizes the bank's financial performance.

Understanding and predicting customer behavior based on machine learning can reveal an increase in online shopping spending, growing interest in investments, the need to develop new digital products, and more. Big Data is used to analyze which financial needs of customers remain unmet or how their cash flows may change under the influence of macroeconomic or technological trends, allowing attractive niches in the banking services market to be identified and innovative products to be developed. The same cash flow forecasts are used by the bank to model the potential volume of cash flows before launching a new product, as well as to assess the associated risks. This allows for informed decisions to be made regarding investments in development and marketing.

Conclusions. The article highlights the problem of improving the efficiency of cash flow management in the banking system of Ukraine, which is particularly relevant in the current conditions. It emphasizes the impact of risks associated with war, rapid development of digital technologies, and European integration requirements on the financial sector. To solve the problem, the study proposes the use of intelligent systems based on Big Data, machine learning, and artificial intelligence for accurate cash flow forecasting. The proposed three-dimensional system for forecasting bank cash flows based on intelligent systems is aimed at improving cash flow forecasting methods using Big Data and machine learning and integrating them into the bank's decision-making system. will not only optimize the bank's daily operations, but also become a strategic tool for risk management and the achievement of long-term development goals.

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Прогнозування грошових потоків банку з використанням інтелектуальних систем

Анотація. Об'єктом дослідження є процеси управління грошовими потоками в банківській системі України, що характеризується високою динамічністю, посиленими ризиками, спричиненими війною та економічною нестабільністю, а також швидкою адаптацією до цифрових технологій і європейських стандартів. Підкреслюється критична важливість ефективного управління грошовими потоками для підтримки фінансової стабільності та забезпечення безперебійної діяльності банку в умовах невизначеності.

Постановка проблеми. Основна проблема, що досліджується у статті, полягає в недостатній ефективності традиційних методів прогнозування та управління грошовими потоками в сучасних реаліях. Ці методи не здатні адекватно обробляти великі обсяги даних, враховувати складні нелінійні залежності та швидко реагувати на непередбачувані зміни, спричинені як війною, так і цифровою трансформацією. Це створює ризики ліквідності, призводить до неоптимального використання капіталу та знижує загальну стійкість банківської системи.

Нерозв'язані аспекти. На сьогодні існують прогалини в інтеграції новітніх інтелектуальних систем безпосередньо в операційні та стратегічні процеси банку. Залишаються невизначеними питання щодо того, як саме перетворити високоточні прогнози, отримані за допомогою машинного навчання, на конкретні, управлінські рішення, що дозволять мінімізувати ризики.

Мета статті. Метою статті є розробка комплексних рекомендацій щодо удосконалення управління грошовими потоками в банку за допомогою інтелектуальних систем. Для цього використовується тривимірний підхід, який поєднує аналіз Big Data, підвищення точності прогнозів за допомогою машинного навчання та їх інтеграцію в систему підтримки прийняття управлінських рішень.

Основний матеріал. Автори статті застосовують тривимірну координатну систему «аналіз-прогнозування-інтеграція» для структуризації дослідження. Розглядаються практичні приклади для прогнозування ліквідності, оцінки платоспроможності позичальників та ефективності маркетингових кампаній. Деталізується використання моделей LSTM, SVM, Random Forest та RNN для підвищення точності прогнозування. Для інтеграції результатів прогнозування в систему ризик-менеджменту банку запропоновані конкретні рішення, такі як використання автоматизованих дашбордів, систем раннього попередження та динамічного скорингу.

Висновки. Запропоновані у статті рекомендації дозволяють банкам перейти від реактивного до проактивного управління грошовими потоками. Це сприяє суттєвому зниженню операційних ризиків, оптимізації капіталу, підвищенню прибутковості та зміцненню конкурентних позицій. Практична цінність дослідження полягає в наданні конкретних інструментів та сценаріїв для впровадження інтелектуальних систем у щоденну діяльність, що є надзвичайно важливим для забезпечення фінансової стійкості банківської системи України в умовах невизначеності.

Ключові слова: *ризик, інтеграція, машинне навчання, ліквідність, фінансова стійкість банку, система ризик-менеджменту банку.*

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