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ARTIFICIAL INTELLIGENCE IN THE PUBLIC DEBT MANAGEMENT SYSTEM

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Abstract. The study is relevant due to the increasing complexity of public debt management amid macrofinancial instability, high borrowing costs, heightened fiscal risks, and the rapid digital transformation of public finances. In such conditions, state institutions need tools that allow them to process large volumes of debt, budget, macroeconomic, and market data more quickly, assess alternative scenarios, and identify threats to debt sustainability in a timely manner. The purpose of the article is to substantiate the opportunities, risks, and directions of using artificial intelligence to increase the analytical capacity of the public debt management system within the digital transformation of public finances. The object of the study is the public debt management system, and the subject is the theoretical, methodological, and applied aspects of integrating AI into the processes of forecasting, scenario analysis, risk management, and management decision support. The methodological basis of the study is a systematic approach, analysis and synthesis, comparative analysis, classification, grouping, scenario approach, risk analysis, scientific abstraction, and graphical modeling. As a result of the study, 12 areas of AI application in public debt management were systematized, namely: forecasting debt dynamics; assessing debt sustainability; modeling currency, interest, and refinancing risks; conducting scenario analysis; optimizing the structure of borrowings; and identifying anomalies in financial data. 8 groups of possibilities for using AI, 10 groups of risks, and corresponding safeguards to minimize them were also identified. An AI-based digital architecture was proposed for a debt management system, comprising 6 functional layers: data layer, analytical layer, decision–support layer, institutional layer, governance layer, and feedback layer. As a result, a conceptual model of AI integration into the public debt management

system was developed, integrating the institutional framework, digital infrastructure, high-quality data, AI analytics, scenario calculations, management decisions, risk control, and debt sustainability monitoring. The practical value of the results lies in their potential use by public finance authorities to develop debt strategies, improve fiscal forecasting, enhance the transparency of analytical procedures, and inform approaches to the responsible use of AI in line with the human-in-the-loop principle.
Keywords: public debt; artificial intelligence; public debt management; debt policy; public finance; digital transformation; debt sustainability; fiscal risks; scenario modeling; GovTech.

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Анотація. Актуальність дослідження зумовлена зростанням складності управління державним боргом в умовах макрофінансової нестабільності, високої вартості запозичень, посилення фіскальних ризиків і швидкої цифрової трансформації публічних фінансів. У таких умовах державні інституції потребують інструментів, які дають змогу швидше обробляти великі масиви боргових, бюджетних, макроекономічних і ринкових даних, оцінювати альтернативні сценарії та своєчасно виявляти загрози борговій стійкості. Метою статті є обґрунтування можливостей, ризиків і напрямів використання штучного інтелекту для підвищення аналітичної спроможності системи управління державним боргом у межах цифрової трансформації публічних фінансів. Об'єктом дослідження є система управління державним боргом, а предметом – теоретико-методичні та прикладні аспекти інтеграції ШІ в процеси прогнозування, сценарного аналізу, ризик-менеджменту та підтримки управлінських рішень. Методологічну основу дослідження становлять системний підхід, аналіз і синтез, порівняльний аналіз, класифікація, групування, сценарний підхід, ризик-аналіз, наукова абстракція та графічне моделювання. У результаті дослідження систематизовано 12 напрямів застосування ШІ в управлінні державним боргом, зокрема прогнозування динаміки боргу,

оцінювання боргової стійкості, моделювання валютного, процентного та рефінансингового ризиків, сценарний аналіз, оптимізацію структури запозичень і виявлення аномалій у фінансових даних. Також визначено 8 груп можливостей використання ШІ, 10 груп ризиків і відповідні запобіжники для їх мінімізації. Запропоновано цифрову архітектуру AI-based debt management system, яка включає 6 функціональних шарів: data layer, analytical layer, decision-support layer, institutional layer, governance layer та feedback layer. В результаті сформовано концептуальну модель інтеграції ШІ в систему управління державним боргом, що поєднує інституційну базу, цифрову інфраструктуру, якісні дані, AI-аналітику, сценарні розрахунки, управлінські рішення, контроль ризиків і моніторинг боргової стійкості. Практична цінність результатів полягає в можливості їх використання органами публічних фінансів для підготовки боргових стратегій, удосконалення фіскального прогнозування, підвищення прозорості аналітичних процедур і формування підходів до відповідального застосування ШІ за принципом human-in-the-loop.
Ключові слова: державний борг; штучний інтелект; управління державним боргом; боргова політика; публічні фінанси; цифрова трансформація; боргова стійкість; фіскальні ризики; сценарне моделювання; GovTech.

Introduction. Public debt management in modern conditions is of particular importance for ensuring the financial stability of the state, macroeconomic stability, and the ability of public finances to respond to crisis phenomena. The growth of government borrowing, the complexity of debt-instrument structures, the rising cost of debt servicing, and increased external uncertainty create a need for better analytical support for debt policy.

The relevance of the study is enhanced by the fact that traditional approaches to public debt management no longer always provide sufficient speed for processing large amounts of financial, budgetary, and macroeconomic information. Under these conditions, artificial intelligence can be an important tool for the digital transformation of public finances, particularly for forecasting the debt burden, assessing fiscal risks, conducting scenario modeling, and supporting management decisions.

The problem is that the potential of artificial intelligence in public debt management remains insufficiently systematized across economics, finance, management, and information technology. On the one hand, AI opens up opportunities to improve forecasting accuracy, enhance analytics transparency, and increase debt management efficiency. On the other hand, its use carries risks related to data quality, algorithmic opacity, cybersecurity, institutional responsibility, and the potential for excessive automation of management processes.

That is why an approach that considers artificial intelligence not as an autonomous mechanism for formulating debt policy but as an analytical tool to support decision-making in the public debt management system requires scientific justification. Such an approach combines the capabilities of digital technologies with the principles of transparency, accountability, and risk-based management, while maintaining the responsibility of state institutions for final decisions in public finance.

Literature Review. The theoretical framework for the study of public debt management is traditionally centered on debt sustainability, borrowing costs, debt portfolio structure, refinancing risks, and the transparency of institutional decision-making. In the recommendations of the International Monetary Fund and World Bank (2014), consider public debt management as the process of formulating and implementing a borrowing strategy that should meet the government's financing needs while considering an acceptable level of risk. At the same time, the World Bank's (2021) methodology for assessing the effectiveness of debt management focuses not only on debt indicators themselves but also on the quality of the institutional architecture, debt accounting systems, cash flow forecasting, operational risks, and the availability of information systems. This is important for this study, as it demonstrates that the digital transformation of debt management cannot be limited to technical software updates, but must encompass data, procedures, accountability, and the quality of management decisions.

Modern global research also emphasizes that the relevance of improving debt management is increasing due to the growth of sovereign debt burdens, the complexity of market conditions, and the increasing role of interest and refinancing risks. OECD (2026) notes that the volume of sovereign debt and borrowing needs remains at historically high levels, increasing the requirements for the quality of forecasting, risk management, and investor communication. Under such conditions, traditional approaches to the analysis of debt dynamics, which rely mainly on retrospective data and linear macro-financial relationships, are not always sufficient to identify risks in a timely manner. That is why the potential of artificial intelligence and machine learning as tools for working with large datasets, identifying hidden relationships, and supporting scenario modeling in public finance is increasingly discussed in the international literature.

A separate area of research concerns the use of AI directly in public finances. OECD (2025a) sees AI as a tool that can enhance fiscal forecasting, risk monitoring, budget data analysis, and increase transparency in public administration. The International Monetary Fund (2025) also emphasizes that integrating AI into public financial management marks a transition from conventional automation to cognitive augmentation of fiscal management, particularly through the analysis of budget documents, forecasting, and the detection of inconsistencies in financial information. At the same time, these approaches are primarily focused on public finances in the broad sense, whereas the specifics of public debt management – the choice of borrowing instruments, the structure of the debt portfolio, debt risks, debt strategy, and coordination with budgetary policy – require separate scientific consideration.

Empirical research on machine learning in debt analysis demonstrates the promise of such tools, but at the same time reveals their limitations. Sica et al. (2023) demonstrate the feasibility of using a random forest to predict fluctuations in the public debt-to-GDP ratio, using Italy as an example. Rafie et Lekhal (2024) apply machine learning methods to assess the sustainability of external public debt for middle-income countries, emphasizing the ability of such models to detect complex nonlinear relationships. Sofianos et al. (2026) propose a hybrid approach that combines DSGE modeling and machine learning for public debt forecasting. These works are important for forming the analytical basis of the study, but they mainly focus on the predictive accuracy of the models, rather than on how the results of such models should be integrated into the institutional framework for debt policy decision-making.

However, the literature on digital governance and financial stability emphasizes that the use of AI in financially significant decisions creates new risks related to data quality, algorithmic opacity, cybersecurity, liability for erroneous recommendations, and possible overreliance on automated conclusions. The Financial Stability Board (2024) and the Bank for International Settlements (2025) highlight that the use of AI in the financial sector without proper controls can increase vulnerabilities and operational risks. Thus, previous studies provide an important analytical basis but leave the issue of the systemic integration of AI, specifically in public debt management, open. This necessitates further research on AI as a tool to support, rather than replace, management decisions, with clear consideration of the principles of transparency, accountability, institutional control, and digital security.

Aims. The aim of the article is to substantiate the conceptual principles for using artificial intelligence as a tool to support management decisions in public debt by systematizing its areas of application, identifying opportunities and risks for public finances, and outlining an approach to the digital transformation of debt management.

Methodology. The methodological basis of the study is based on a combination of the provisions of the theory of public debt management, the concept of debt sustainability, risk management approaches in public finance, and modern approaches to digital governance and the responsible use of artificial intelligence. Public debt management in the article is considered as an institutional and analytical system that covers the formation of a debt strategy, management of the structure of the debt portfolio, monitoring of interest, currency and refinancing risks, as well as ensuring transparency and accountability of management decisions, which is consistent with the approaches of the International Monetary Fund and World Bank (2014) and the World Bank (2021).

To achieve the study's goal, a systematic approach was used, enabling consideration of artificial intelligence not as a separate technological tool but as an element of a broader public finance management system, encompassing data, institutions, analytical procedures, managerial responsibility, and risk control. Methods of analysis and synthesis were used to generalize scientific and applied approaches to the digital transformation of public finances and public debt management; the comparison method was used to compare the traditional logic of debt management with the capabilities of analytical tools based on artificial intelligence; the classification and grouping method was used to systematize the areas of application of AI, the expected benefits and potential limitations of its use.

The study also used a risk-based approach, which allowed identifying technological, informational, institutional, financial, ethical, and cybersecurity risks of integrating AI into public debt management processes. The scenario approach was used to substantiate the role of artificial intelligence in modeling alternative debt policy trajectories, assessing the impact of macro-financial shocks, and preparing an analytical base for medium-term management decisions. The method of scientific abstraction was used to form a conceptual vision of an AI-based debt management system, in which AI serves as an intellectual analytical layer but does not replace the institutional responsibility of state bodies.

Since the article is of a theoretical and applied nature, it does not develop the author's economic and mathematical model or apply complex statistical procedures. The theoretical framework of the study is based on the logic of the relationships among data quality, AI analytical capabilities, debt risks, institutional control, and the effectiveness of management decisions. This approach makes it possible to test the research hypothesis that artificial intelligence can increase the efficiency of public debt management only if technological capabilities are combined with algorithmic transparency, data quality, cybersecurity, and the maintenance of human responsibility for final decisions.

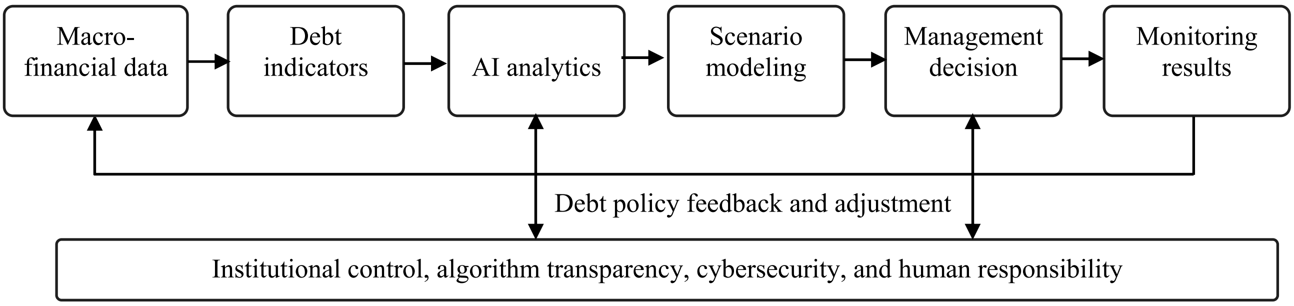
Results. Within the framework of the study, the results are formed as a sequence of theoretical and applied generalizations that reflect the place of artificial intelligence in the public debt management system, the directions of its possible application, the digital architecture of the corresponding system, information prerequisites, opportunities, risks, and conceptual principles of integrating AI into public finance processes. The first result is the definition of AI's functional role in debt management as an analytical tool to support management decisions (OECD, 2025a, 2025b; Pattanayak et al., 2026).

The public debt management system encompasses a set of interrelated processes related to planning public borrowing, selecting sources of financing, managing debt service costs, controlling currency, interest rate, and refinancing risks, monitoring debt sustainability, and preparing medium-term debt strategies. In the traditional model, these processes are mainly based on statistical indicators, macroeconomic forecasts, expert assessments, and regulated decision-making procedures. In the context of increasing uncertainty, instability of financial markets, and increased fiscal risks, such a system requires expanding analytical capacity through digital tools (Blanchard, 1990; Bohn, 1998; International Monetary Fund & World Bank, 2014; World Bank, 2021).

Artificial intelligence in this system should be considered not as an independent mechanism for forming debt policy, but as an analytical layer that integrates data sets, algorithmic processing, forecasting, scenario analysis, and the preparation of management decision options. Its role is to increase the speed and accuracy of information processing, identify hidden dependencies between debt, budget, macroeconomic, and market indicators, as well as to form a more structured information base for bodies responsible for public debt management (Agrawal et al., 2019; Athey & Imbens, 2019; Mullainathan & Spiess, 2017; Varian, 2014).

In the functional dimension, AI can be integrated into several key stages of debt management: data collection and verification, debt dynamics forecasting, debt sustainability assessment, borrowing cost modeling, sensitivity analysis to currency and interest rate shocks, preparation of alternative debt policy scenarios, and ongoing monitoring of its implementation results. Such integration does not change the institutional responsibility of state bodies, but expands their ability to work with large data sets and complex options for the development of the macrofinancial environment (Mutai et al., 2025; Rafie & Lekhal, 2024; Sica et al., 2023; Sofianos et al., 2026; Zarkova, 2023).

The role of artificial intelligence in the public debt management system can be presented as a sequential process of transition from data to management decision. This logic assumes that macro-financial and debt data undergo algorithmic processing, after which they are used to generate scenarios, inform management decisions, monitor results, and further adjust debt policy. A generalized scheme of this process is shown in Figure 1.



Source: compiled by the authors.

Figure 1. The place of artificial intelligence in the public debt management system

The above diagram captures the auxiliary yet system-forming nature of AI within debt management: it does not replace political, legal, and institutional decisions, but provides the information and analytical justification for them. The central element of this role is transforming disparate macro-financial data into structured scenarios to select an acceptable trajectory for public borrowing, optimize the debt structure, and respond to fiscal risks in a timely manner.

The peculiarity of this approach is that using AI in the field of public debt requires a constant interplay between technological and managerial logic. On the one hand, algorithmic tools provide data processing, pattern detection, and the preparation of forecast scenarios. On the other hand, final decisions on the volume, structure, cost, and terms of public borrowing remain the responsibility of authorized state institutions. That is why the effectiveness of the use of AI depends not only on the quality of the digital infrastructure, but also on the availability of institutional control rules, transparency of models, cybersecurity, and human responsibility mechanisms (European Parliament & Council of the European Union, 2024; National Institute of Standards and Technology, 2023).

Therefore, the first result of the study is the definition of AI as a tool for strengthening the public debt management system analytically. In this role, it performs data processing, forecasting, scenario modeling, decision support, and monitoring of results, but does not assume responsibility for forming public debt policy. This provides a basis for further systematization of specific areas of AI application in debt management.

The second result of the study is to systematize the main areas of use of artificial intelligence in public debt management. Such systematization is necessary because AI can perform different functions at different stages of debt management, ranging from processing primary financial data to preparing analytical scenarios for strategic management decisions. In this study, AI applications are grouped by their functional purpose within the debt policy system.

Public debt management involves the ongoing alignment of a country's financing needs with acceptable levels of cost and risk. In this context, AI can be used to enhance those elements of debt management that rely on large datasets, complex relationships among macroeconomic indicators, rapidly changing market conditions, and the need to compare alternative scenarios. At the same time, each application area has not only the expected management effect, but also certain limitations that must be taken into account when implementing such tools in practice (International Monetary Fund, 2022; International Monetary Fund & World Bank, 2014; European Commission, 2024).

To summarize the results, Table 1 presents the author's classification of the areas of application of artificial intelligence within the public debt management system. The table combines the functional area of AI use, its content, the expected result for management practice, and potential limitations that may affect the quality and reliability of such an application.

Table 1

Directions of application of artificial intelligence in the public debt management system

Direction of application	The content of using AI	Expected management result	Potential limitations
Forecasting the dynamics of public debt	Building forecasts for changes in the volume of public debt, its ratio to GDP, budget revenues, and other macrofinancial indicators	Formation of more substantiated medium-term estimates of the debt burden and timely identification of risks of its growth	The dependence of the results on the quality of macroeconomic assumptions, the completeness of historical data, and the ability of the models to take into account shock events
Debt sustainability assessment	Analysis of the debt trajectory taking into account economic growth rates, budget deficits, interest rates, exchange rates, and refinancing needs	Increasing the accuracy of assessing the state's ability to meet debt obligations without accumulating critical fiscal imbalances	The difficulty of formalizing political, security, and institutional factors that affect debt sustainability
Forecasting debt service costs	Estimating future interest payments on domestic and external debt, taking into account the structure of the instruments, maturity dates, and market conditions	Improving budget planning and reducing the risk of underestimating future debt service expenditures	Sensitivity of forecasts to volatility in interest rates, exchange rates, and conditions of access to financial markets
Currency risk modeling	Identifying the impact of exchange rate fluctuations on the volume of debt, its servicing costs, and budget financing needs	Supporting decisions on the optimal currency structure of public debt and reducing vulnerability to devaluation shocks	The presence of external factors that are difficult to predict by models, in particular geopolitical risks and sharp changes in the balance of payments
Interest rate risk modeling	Estimating the impact of changes in market rates on the cost of new borrowing and servicing floating-rate debt	Justification of decisions regarding the ratio of fixed and floating rate instruments, as well as the choice of borrowing terms	Limited predictability of monetary policy, global financial conditions, and investor behavior during periods of instability
Refinancing risk assessment	Analysis of the debt repayment schedule, the concentration of payments over time, and the need for new borrowing to cover previous debts	Identifying periods of peak debt burden and preparing decisions to smooth the repayment schedule	Risk of misjudgment of future access to capital markets and conditions of official financing
Debt policy scenario analysis	Formation of alternative scenarios for the development of the debt situation under different assumptions regarding the budget deficit, economic growth, inflation, exchange rate and interest rates	Comparing possible debt trajectories and choosing a more sustainable debt policy configuration	Scenarios cannot fully capture all unforeseen shocks and depend on the correctness of the assumptions made

End of Table 1

Direction of application	The content of using AI	Expected management result	Potential limitations
Optimization of the structure of public borrowing	Analysis of the ratio of domestic and external borrowings, maturity, currency structure, types of instruments and cost of financing	Improving the balance of the debt portfolio from the standpoint of value, risk, liquidity and long-term sustainability	Limitations related to the availability of financial instruments, the depth of the domestic market and the conditions of international support
Fiscal risk monitoring	Identifying signals of potential increases in debt burden due to fiscal imbalances, government guarantees, quasi-fiscal liabilities, or external shocks	Creating an early warning system for risks that could worsen the state of public finances	Incomplete data on contingent liabilities, state-owned enterprises, and extra-budgetary risks
Automated preparation of analytical reporting	Automation of debt data processing, generation of analytical reports, identification of key changes in the debt structure, and preparation of regular reviews	Increasing the speed of preparation of analytical materials and reducing the operational burden on state institutions	The need for human verification of results, the risk of errors in case of incorrect data loading or interpretation
Detecting anomalies in debt and budget data	Identifying unusual changes, gaps, errors, or potentially risky deviations in financial data sets	Improving the quality of data control, preventing technical errors and strengthening the reliability of the analytical base	Possibility of false signals, especially in conditions of unstable statistics or sharp structural changes in financial flows
Increasing transparency of public finances	Using digital tools to present debt information in a structured way, explain scenarios, and communicate risks to stakeholders	Strengthening the openness of debt policy, increasing the trust of investors, international partners and society in the management of public finances	The need to ensure explainability of algorithms, protect sensitive data, and align communication with official state policy

Source: compiled by the authors.

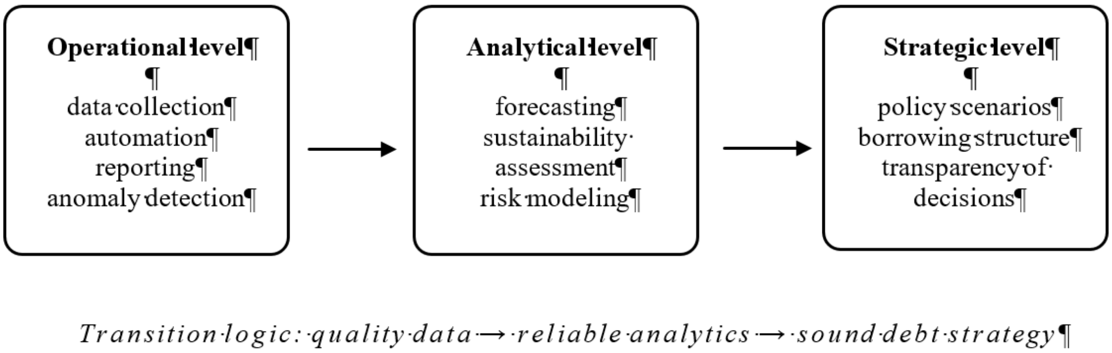
The above classification shows that the areas of application of AI in public debt management are not limited to forecasting individual debt indicators. They cover the full cycle of debt management: from the formation of an information base and data quality control to scenario analysis, risk assessment, support for management decisions and communication of debt policy results.

The generalization of the areas of application of AI also indicates the need to distinguish three levels of its use. The first level is related to operational support: data processing, reporting automation and detection of technical errors. The second level covers analytical functions: forecasting, assessing debt sustainability, modeling currency, interest rate and refinancing risks. The third level is strategic in nature and concerns the preparation of debt policy scenarios, optimizing the structure of borrowing and increasing the transparency of public finance management.

To visually summarize the functional classification, Figure 2 presents three levels of AI application in public debt management, reflecting a gradual transition from operational support to strategic use of analytics results.

The operational, analytical, and strategic levels are not isolated: each subsequent level relies on the quality of the previous one, and therefore the strategic value of AI depends on the reliability of data, models, and control procedures.

Thus, the second result of the study is the formation of a functional classification of the areas of use of AI in public debt management. It creates the basis for further definition of the digital architecture of the AI-based debt management system, since the practical implementation of the indicated areas requires a clear understanding of what data, analytical modules, institutional connections and control mechanisms should ensure the operation of such a system.



Source: compiled by the authors.

Figure 2. **Levels of AI application in public debt management**

The third result of the research is the formation of a digital architecture AI-based debt management system, which reflects the logic of integrating artificial intelligence into the public debt management system. Such an architecture should combine technological components, information flows, analytical models, institutional procedures and control mechanisms, since the effectiveness of AI application in the public debt sector depends not only on the quality of algorithms, but also on the ability of public institutions to use the obtained analytical results in the process of preparing and implementing debt policy (OECD, 2025a; World Bank, 2021, 2023).

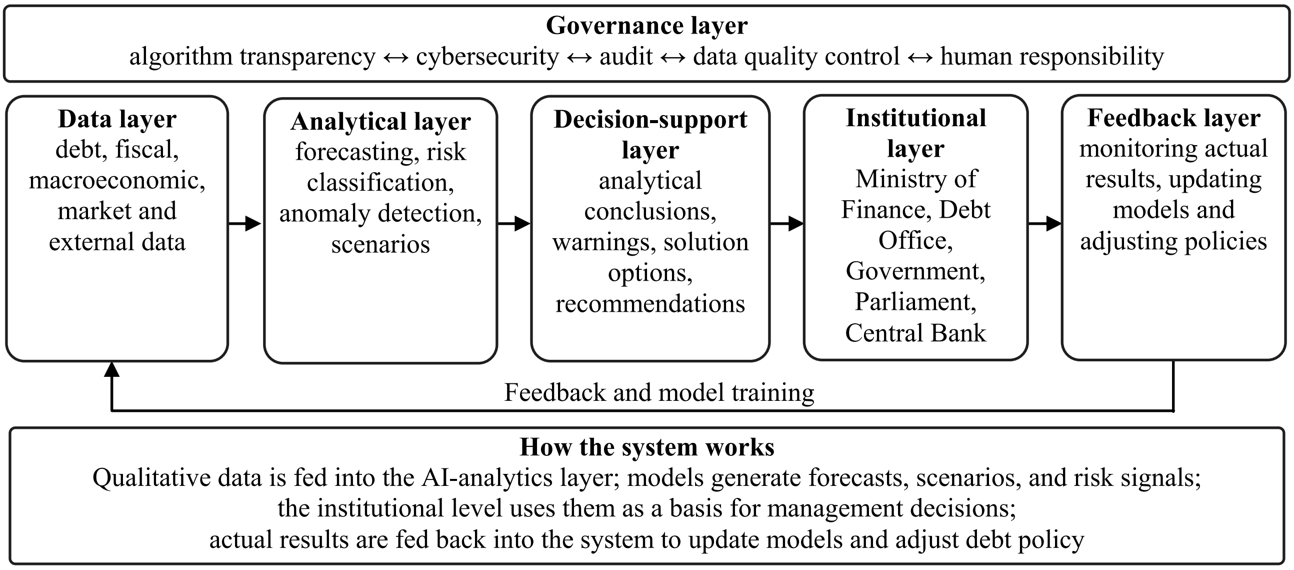
The proposed architecture is based on the assumption that public debt management is a sequential process of transforming data into management decisions. At the first stage, an array of debt, budget, macroeconomic, market and foreign economic data is formed. At the second stage, this data is processed using analytical AI models that can provide forecasting, risk classification, anomaly detection and modeling of alternative scenarios. At the third stage, the results of the analytics are converted into an information basis for supporting management decisions, however, the decisions themselves remain within the sphere of responsibility of authorized state bodies.

In the structural dimension, it is appropriate to represent an AI-based debt management system as a set of six interconnected layers: data layer, analytical layer, decision – support layer, institutional layer, governance layer and feedback layer. Data layer provides accumulation, verification and updating of data. Analytical layer is responsible for application of forecasting algorithms, risk analysis and scenario modeling. Decision-support layer transforms analytics results into reports, risk signals, scenario conclusions and management action options. Institutional layer defines entities responsible for use of these results. Governance layer provides transparency, audit, cybersecurity and quality control of algorithms. Feedback layer allows to compare forecast estimates with actual results and to adjust models (Araujo et al., 2024; Bank for International Settlements, 2024; Pattanayak et al., 2026).

To visualize the relationship between these elements, Figure 3 presents the digital architecture of an AI-based debt management system, within which AI plays the role of an analytical core that connects information flows with the process of preparing management decisions.

The proposed scheme shows that the digital architecture of public debt management using AI should function as a closed loop. The input element is data that goes through the stage of cleaning, structuring and analytical processing. The result of the analytical layer is not an automatic solution, but a set of predictive assessments, scenarios, warnings and options for action that can be used to prepare a debt strategy, a borrowing plan, risk management and communication with financial market participants.

The key prerequisite for the functioning of such a system is the quality and completeness of data. In the field of public debt, data have a different nature: some of them are formed in the debt accounting system, some depend on the budget process, some come from financial markets, and some reflect external macroeconomic and geopolitical conditions. That is why the data layer should include not only the initial accumulation of information, but also procedures for its verification, unification, regular updating and consistency control (European Commission, 2024; Gasanov, 2023; International Monetary Fund, 2022).



Source: compiled by the authors.

Figure 3. **Digital architecture of AI-based debt management system**

To systematize the information basis of the proposed architecture, Table 2 lists the main data groups that can be used by an AI-based debt management system, as well as the corresponding management tasks and data quality risks.

Table 2

Data required for the operation of an AI-based debt management system

Data group	Examples of indicators	Management tasks	Data quality risks
Debt data	The volume of public and state-guaranteed debt; domestic and external debt; currency, maturity, rate, repayment schedule; structure of debt instrument owners	Forecasting debt burden; assessing the structure of the debt portfolio; managing refinancing risk; preparing a borrowing plan	Incomplete historical series; different approaches to debt classification; update delays; data consolidation errors
Budget data	Revenues, expenditures, budget deficit, primary balance, financing needs, debt service expenditures	Assessing the need for borrowing; aligning debt policy with budget planning; analyzing fiscal space	Discrepancy between planned and actual indicators; data fragmentation; changes in budget classification
Macroeconomic data	GDP, inflation, exchange rate, balance of payments, employment rate, economic growth, trade indicators	Scenario modeling of debt dynamics; assessment of debt sustainability; analysis of the impact of macrofinancial shocks	Review of statistical estimates; high volatility of indicators; presence of lags in data publication
Market data	Yield on government securities, demand at auctions, spreads, market liquidity, investor expectations	Optimization of borrowing terms; assessment of the cost of debt; selection of maturity and placement instruments	Market volatility; limited liquidity; impact of short-term information shocks
Currency and interest data	Interest rates, yield curves, exchange rates, share of debt in foreign currency, sensitivity to rate changes	Currency and interest rate risk modeling; debt service cost estimation; stress scenario analysis	Instability of market expectations; different data sources; risk of incorrect transfer of short-term trends

End of Table 2

Data group	Examples of indicators	Management tasks	Data quality risks
Data on government guarantees and contingent liabilities	State guarantees, obligations of state-owned enterprises, potential fiscal risks, quasi-fiscal transactions	Monitoring hidden debt risks; assessing the potential impact of contingent liabilities on public finances	Insufficient detail; incomplete reporting; difficulty in assessing the likelihood of risks occurring
Data on international financial assistance	Loans from international financial organizations, grants, macro-financial assistance, program conditions, receipt and repayment schedules	Planning external financing; assessing dependence on official creditors; coordinating debt policy with international programs	Changes in financing conditions; political uncertainty; time gaps between commitments and actual receipts
Data on fiscal risks	Risks of revenue shortfalls, expenditure overruns, banking and energy risks, demographic and social obligations	Early identification of threats to debt sustainability; assessment of the need for additional financing; preparation of preventive measures	Difficulty of quantitative measurement; incomplete information; high dependence on expert assumptions
Environmental data	Global interest rates, energy prices, geopolitical risks, ratings, conditions for access to international capital markets	Assessment of external shocks; modeling of alternative scenarios for access to financing; analysis of risks for debt strategy	High uncertainty; difficulty in formalizing political factors; risk of rapid loss of data relevance

Source: compiled by the authors.

The systematization of data groups shows that an AI-based debt management system should be based on the integration of internal state information resources with external market and macroeconomic data. Within such an architecture, data quality becomes an independent management prerequisite, since errors, delays, or incomplete information can directly affect the forecasting results and the quality of the prepared recommendations.

Therefore, the third result of the research is the formation of a digital architecture of AI-based debt management system, which combines information, analytical, managerial, institutional and control components. Such architecture creates a basis for further identification of the possibilities of using AI in increasing the efficiency of debt policy and for assessing the risks associated with its integration into the sphere of public finances.

Determining the functional place of artificial intelligence in the public debt management system and forming a digital architecture for its use make it possible to proceed to the systematization of potential opportunities that are created for debt policy. Within the framework of this study, such opportunities are considered not as separate technological effects, but as a set of analytical, forecasting, managerial, institutional and communication results that can improve the quality of preparation and implementation of decisions in the field of public finance (International Monetary Fund, 2025; Maslej et al., 2024; OECD, 2025b).

Public debt management requires constant reconciliation of the state's current financial needs, borrowing costs, debt currency structure, maturity, fiscal constraints, and macroeconomic risks. The use of AI expands the possibilities of working with these parameters due to the ability to quickly process large sets of heterogeneous data, generate alternative scenarios, detect deviations from expected trends, and provide analytical support for medium-term and strategic planning.

For the purposes of this study, the possibilities of using AI in debt policy are grouped by functional criterion. This approach allows us to show what kind of managerial effect can be obtained from the application of intelligent technologies in different components of the public debt management system. A generalized description of such possibilities is presented in Table 3.

Table 3

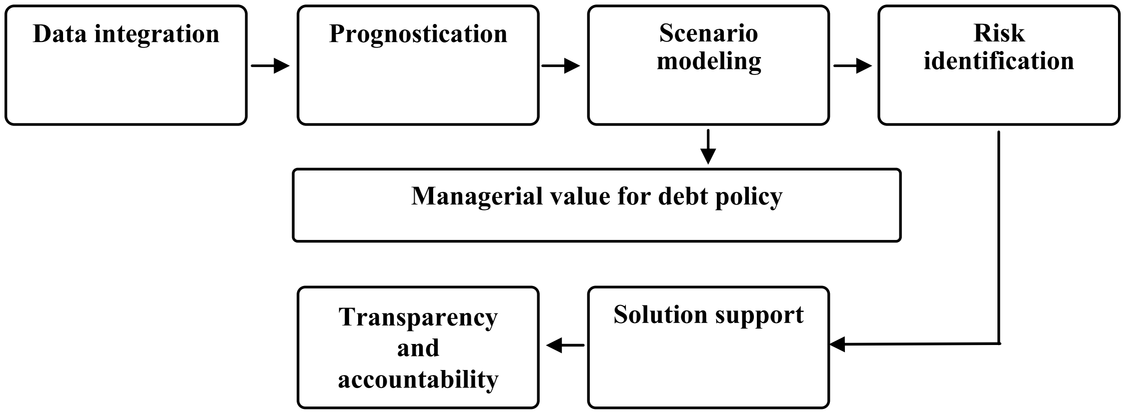
Possibilities of using AI in the field of public debt management

Opportunity group	Content of AI usage possibilities	Potential impact on public finances
Analytical capabilities	Processing large amounts of macroeconomic, budgetary, debt, market and foreign economic data; integrating information from various sources into a single analytical environment	Increasing the completeness of the information base for decision-making; reducing the fragmentation of debt analysis; forming a holistic picture of the state of public finances
Forecasting capabilities	Building forecasts of the dynamics of public debt, its servicing costs, interest rates, exchange rates, budget deficits, and financing needs	Improving the quality of medium-term planning; early identification of potential imbalances; increasing preparedness for changing macro-financial conditions
Scenario possibilities	Formation of alternative debt policy scenarios taking into account different assumptions regarding economic growth, inflation, exchange rate, cost of borrowing and access to financing	Comparing the consequences of different management decisions; preparing more flexible debt strategies; reducing the risk of single-option planning
Risk-based opportunities	Automated identification of currency, interest rate, refinancing, liquidity and fiscal risks; monitoring of deviations from target parameters of the debt strategy	Strengthening the early warning system; improving the quality of risk control; timely adjustment of government borrowing parameters
Management capabilities	Preparation of analytical panels, recommendation scenarios, automated signals and information materials for decision-makers	Reducing the time between obtaining data and preparing a management response; increasing the validity of decisions; strengthening the role of evidence -based management
Institutional capabilities	Standardization of analytical procedures, strengthening coordination between public finance management bodies, and developing unified approaches to debt risk analysis	Increasing institutional capacity for debt management; reducing dependence on disparate expert assessments; improving consistency of decisions
Technological capabilities	Automation of part of reporting, settlement and monitoring procedures; detection of anomalies in data; integration with digital budget planning and treasury services systems	Reducing operational workload; increasing the speed of debt analytics preparation; improving the quality of data control
Communication capabilities	Visualizing debt indicators, preparing understandable analytical materials, supporting open data, and explaining the impact of debt policy on public finances	Increasing the transparency of debt policy; strengthening the trust of investors, international partners and society; improving the accountability of public administration bodies

Source: compiled by the authors.

The presented systematization shows that the possibilities of using AI in the field of public debt management are multi-level in nature. They cover not only the technical automation of individual operations, but also the preparation of an analytical basis for forecasting, scenario modeling, risk control, inter-institutional coordination, and increasing the transparency of debt policy (Agrawal et al., 2019; Mullainathan & Spiess, 2017; OECD, 2025b).

To illustrate how individual AI capabilities translate into management outcomes, Figure 4 presents the chain of AI management value creation for debt policy.



Data and forecasts are transformed into scenarios, risk signals, solutions, and transparent communication

Source: compiled by the authors.

Figure 4. **AI management value chain for debt policy**

The practical value of AI is not formed at one stage, but as a result of a consistent combination of data integration, forecasting, scenario modeling, early risk identification, decision support, and increased transparency of debt policy.

Of particular importance is that AI can strengthen the relationship between debt policy, budget planning and macro-financial forecasting. In the traditional system, these elements are often analyzed sequentially or within separate functional blocks. Intelligent technologies make it possible to form a more integrated view of the impact of borrowing, debt service costs, budget deficits, currency fluctuations and external shocks on the overall state of public finances (Pattanayak et al., 2026; World Bank, 2023).

At the same time, these opportunities cannot be realized automatically through the implementation of technological solutions alone. Their practical value depends on the quality of data, the level of digital maturity of institutions, the availability of methodologically agreed procedures, the transparency of algorithms, and the ability of responsible bodies to use the results of AI analysis in the process of preparing decisions. This forms the basis for moving to the next stage of research – the systematization of the risks and limitations of using AI in the field of public debt.

The use of artificial intelligence in public debt management creates not only new analytical and management opportunities but also several risks that must be considered during the digital transformation of public finances. Unlike many corporate financial decisions, decisions in the field of public debt are systemic, affecting fiscal sustainability, budget obligations, the cost of public borrowing, investor confidence, and the state's long-term financial security. Therefore, the use of AI in this area requires not only technological readiness, but also clear institutional, legal, and managerial safeguards (Bank for International Settlements, 2025; Danielsson & Uthemann, 2024; European Central Bank, 2024; Financial Stability Board, 2024).

AI risks in the debt management system should be considered as a multi-level set of technological, information, cybersecurity, institutional, ethical, legal, and managerial constraints. Their occurrence may be associated with both the internal characteristics of the algorithms themselves and the quality of data, the level of digital maturity of state bodies, insufficient transparency of models, weak coordination between institutions, or excessive trust in automated recommendations. In this regard, within the framework of the study, the risks of using AI are systematized considering their possible consequences for debt policy and public finances (European Parliament & Council of the European Union, 2024; National Institute of Standards and Technology, 2023).

The problem of demarcating the analytical function of AI and the responsibility of state institutions for the final decision requires special attention. AI can generate forecasts, detect deviations, model alternative scenarios, or provide warning signals, but it should not replace the political, fiscal, and managerial responsibility of the bodies that formulate and implement debt policy. A general description of the main risks and limitations of applying AI in the field of public debt is presented in Table 4.

Table 4

Risks of using AI in the public debt management system and possible safeguards

Risk group	Risk content	Possible consequences	Safeguards
Technological risks	Algorithm errors, incorrect model settings, software instability, or insufficient adaptation of AI solutions to the specifics of public finances	Formation of inaccurate forecasts, distortion of the assessment of debt dynamics, and preparation of false analytical signals for management decisions	Model testing, regular validation of results, use of multiple analytical approaches, technical audit, and gradual implementation of AI solutions
Information risks	Incompleteness, untimeliness, fragmentation, or low quality of macroeconomic, budgetary, debt, market, and external economic data	Incorrect determination of financing needs, underestimation of debt burden, distortion of assessment of currency, interest, and refinancing risks	Data standardization, formation of unified registers, information quality control, regular updating of databases, and documentation of information sources
Cyber risks	Unauthorized access to debt and budget data, manipulation of input data, attacks on digital infrastructure, or violation of the integrity of analytical systems	Breach of confidentiality, reduced trust in government financial information, risk of destabilization of debt management processes, and communication with investors	Cyber protection of critical financial infrastructure, data backup, multi-level access, independent security audit, and constant monitoring of digital threats
Institutional risks	Insufficient digital maturity of government agencies, weak coordination between institutions, shortage of specialists capable of combining knowledge in the field of debt management and digital technologies	Formal implementation of AI without real impact on the quality of management, duplication of functions, inconsistency of analytical procedures, and reduced decision-making efficiency	Development of institutional capacity, interdepartmental coordination, training of personnel, creation of methodological standards, and identification of responsible units
Management risks	Overreliance on automated inference, use of AI recommendations without proper expert review, or insufficient understanding of the limitations of the models	Reducing the role of professional judgment, making decisions based on unverified recommendations, and weakening the responsibility of officials for the results of debt policy	The human-in-the-loop principle, mandatory expert verification of results, separation of analytical support, and final management decision
Ethical risks	Opacity of algorithms, difficulty in explaining results, possible biases in models, and the use of evaluation criteria that are not sufficiently understood or are unsuitable for the public sector	Reduced accountability, increased complexity of public control, and distrust of digital solutions in the field of public finance	Use of explainable AI, disclosure of model logic within acceptable limits, ethical standards for the use of AI, and independent evaluation of algorithmic solutions
Legal risks	Lack of or insufficient clarity of regulatory rules regarding the use of AI in public finance, data processing, liability for automated inferences, and model auditing	Legal uncertainty, difficulty in establishing liability, and limitations on the use of AI result in formal management procedures	Developing regulatory requirements for the use of AI, addressing issues of liability, data protection, algorithm auditing, and maintaining management control

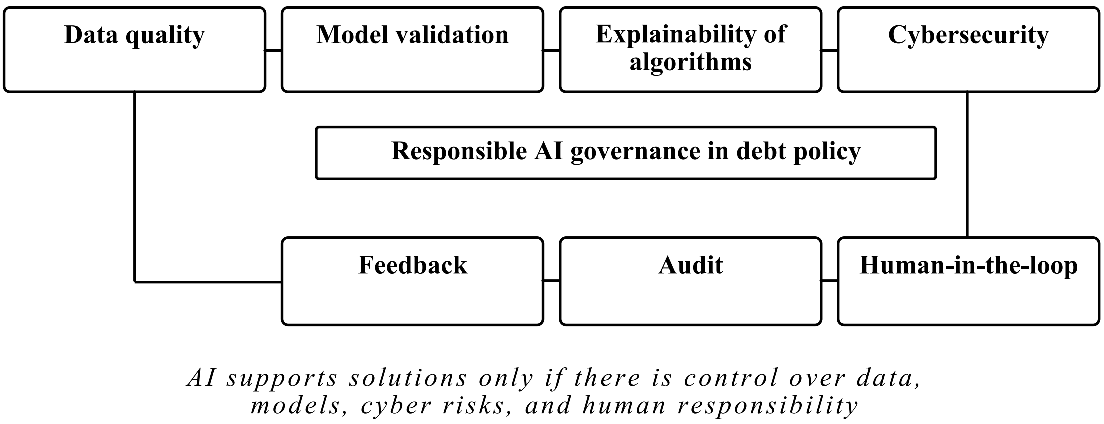
End of Table 4

Risk group	Risk content	Possible consequences	Safeguards
Risks of algorithmic opacity	Using models whose logic is difficult to explain or unavailable for verification by responsible authorities, auditors, or external stakeholders	Limited ability to verify the basis of forecasts and recommendations, difficulty in controlling the quality of analytical conclusions, and increased risk of erroneous decisions	Model documentation, transparent methodological assumptions, change logging, model version control, and regular external evaluation of their results
Risks of excessive automation	Transferring too many of the analytical and preparatory procedures to automated systems without proper integration with expert judgment	Weakening of institutional expertise, loss of ability to critically evaluate model results, dependence on digital infrastructure	Gradual automation, preservation of expert functions, staff training, duplication of key procedures by manual or alternative verification
Risks of false forecasting	The inability of models to properly account for extreme events, geopolitical shocks, abrupt changes in market conditions, crisis scenarios, or structural shifts in the economy	Underestimation of borrowing needs, wrong choice of debt structure, untimely response to deterioration in debt sustainability	Stress testing, scenario analysis, regular updating of assumptions, combining AI forecasts with macroeconomic expertise and crisis scenarios

Source: compiled by the authors.

The above systematization shows that the risks of applying AI in the field of public debt are not limited to technical problems of the functioning of algorithms. A significant part of the risks is associated with the institutional environment, data quality, regulatory certainty, digital security, the ability to explain model results, and the preservation of human responsibility for final decisions in debt policy.

To summarize the safeguards needed to minimize the risks of using AI, Figure 5 outlines the responsible use of AI in the area of public debt.



Source: compiled by the authors.

Figure 5. **Outline of responsible use of AI in the area of public debt**

Responsible use of AI in debt management should be based on a closed-loop management approach that includes data quality, model validation, algorithm explainability, cybersecurity, human-in-the-loop, auditing, and continuous feedback (Financial Stability Board, 2024; National Institute of Standards and Technology, 2023).

A key limitation of using AI is that even the most advanced models cannot fully account for political, geoeconomic, security, and crisis-related factors that significantly affect government borrowing, debt-servicing costs, and investor expectations. Therefore, the results of AI analysis should be used as an element of analytical support, and not as a stand-alone basis for automated decisions on the structure, timing, cost, or sources of government financing (Bank for International Settlements, 2025; Danielsson & Uthemann, 2024; Financial Stability Board, 2024).

To mitigate the risks of integrating AI into the public debt management system, a combination of technological, institutional, and regulatory safeguards is needed. These include data quality control, model validation, cybersecurity, algorithm auditing, explainability of results, accountability, and the maintenance of the human-in-the-loop principle. It is this combination that allows us to consider AI not as an autonomous mechanism for formulating debt policy, but as a tool that can strengthen the state's analytical capacity, provided it is properly controlled.

Therefore, the results of the risk and limitation systematization form the basis for developing a holistic conceptual model for integrating AI into the public debt management system. Such a model should combine the areas of application of intelligent technologies, digital architecture, information base, management capabilities, and a system of safeguards necessary for the responsible use of AI in public finances.

Based on the identified areas of application of AI, digital architecture of the system, necessary information base, opportunities, risks, and limitations, a conceptual model of integration of artificial intelligence into the public debt management system is proposed. Its purpose is to combine technological, analytical, institutional, and control elements into a single sequence that ensures the use of AI as a decision-support tool in debt policy (Petrukha, Petrukha, & Miakota, 2024a, 2024b; Petrukha et al., 2025).

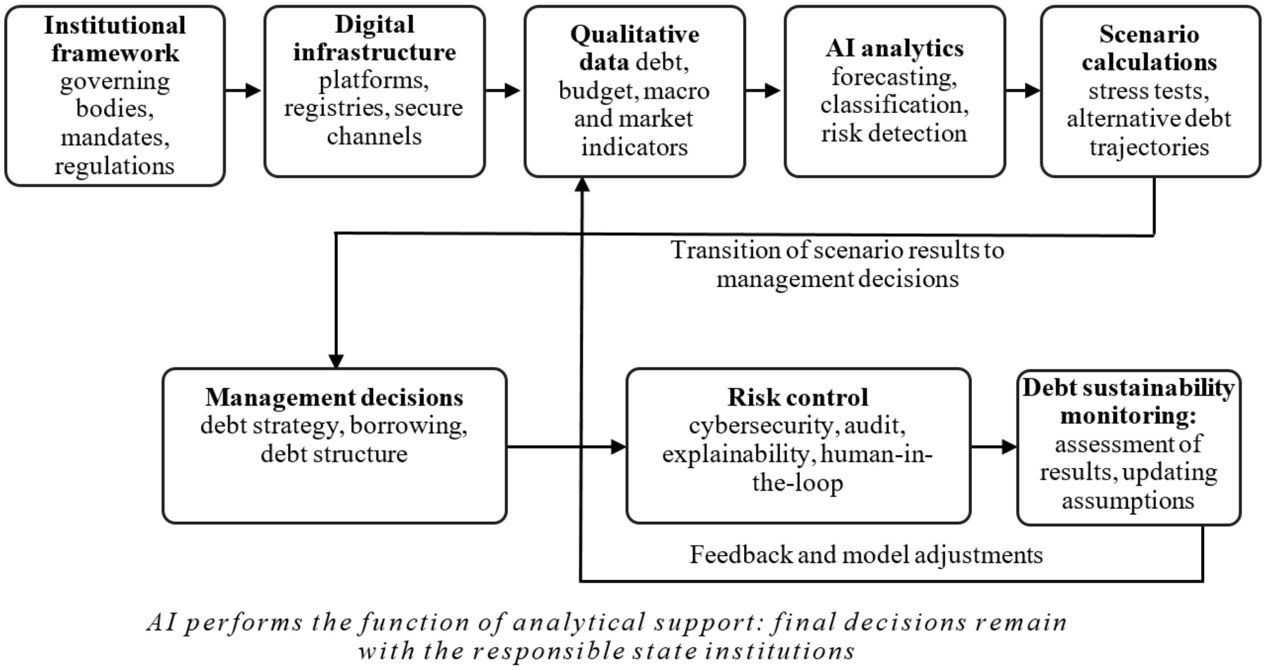
The proposed model is based on the assumption that the effectiveness of AI in debt management depends not only on the availability of forecasting algorithms or software solutions but also on the maturity of the institutional environment, data quality, security of the digital infrastructure, transparency of methodological assumptions, regular verification of models, and the responsibility of state bodies for final management decisions. In this logic, AI does not act as an independent subject of debt policy, but as an auxiliary analytical mechanism within the broader system of public finances (Petrukha et al., 2026).

The conceptual model includes eight interconnected blocks: institutional framework, digital infrastructure, qualitative data, AI analytics, scenario calculations, management decisions, risk control, and debt sustainability monitoring. The sequence of these blocks reflects the progression from organizational and technological prerequisites to the practical use of AI-generated analysis results in the process of preparing decisions on public borrowing, debt structure, debt-servicing costs, and risk management.

A graphical representation of the conceptual model of AI integration into the public debt management system is shown in Figure 6. Such visualization allows us to show not only the sequence of the main elements but also the presence of feedback, without which the use of AI in debt policy cannot be sufficiently adaptive to changing macroeconomic, fiscal, and market conditions.

Within the proposed model, the institutional framework forms the organizational boundaries of the use of AI and defines the roles of public debt management entities. This block includes bodies responsible for forming debt policy, preparing medium-term strategies, planning public borrowing, monitoring debt risks, and ensuring reporting. The institutional block is initial, since it is what determines which decisions can be supported by AI, what data can be used, who is responsible for checking the results, and to what extent automated analytics can be included in the management process.

Digital infrastructure provides the technical conditions for the functioning of an AI-based debt management system. It includes information platforms, digital registries, secure data exchange channels, and integration tools between budget, debt, macroeconomic, and market databases. Without the right infrastructure, the application of AI may remain fragmented, as models will not have stable access to up-to-date, complete, and standardized data necessary for forecasting and scenario analysis (Petrukha, Petrukha, Mykolaichuk, et al., 2026; Petrukha, Petrukha, Stoliarenko, et al., 2026).



Source: compiled by the authors.

Figure 6. **Conceptual model of AI integration into the public debt management system**

The qualitative data block is the information basis of the model. It includes data on the volume and structure of public debt, repayment schedules, currency structure of obligations, interest rates, debt service expenditures, budget indicators, macroeconomic forecasts, market conditions, government guarantees, international financial assistance, and other factors affecting debt sustainability. The quality of this block determines the reliability of subsequent AI analytics, as errors or gaps in the input data can propagate into forecasts, risk signals, and scenario calculations.

AI analytics in the proposed model performs forecasting, risk classification, anomaly detection, assessment of the sensitivity of debt indicators to changes in macroeconomic conditions, and preparation of preliminary analytical signals. At this stage, AI can be used to process large amounts of information, identify hidden dependencies among debt, budget, and market indicators, and serve as the basis for scenario calculations. At the same time, the results of AI analytics should be suitable for verification, documentation, and expert explanation.

Scenario calculations are the next functional block of the model. They allow for the estimation of possible trajectories of public debt under different assumptions about economic growth, exchange rates, interest rates, financing volumes, budget deficits, access to external markets, and international support. In this block, AI can be used to quickly compare alternative scenarios, assess the impact of shocks, and identify potential points of deterioration of debt sustainability.

Management decisions in the model involve using AI analysis results to prepare a debt strategy, plan government borrowing, determine an acceptable debt structure, select financing sources, estimate the cost of debt service, and prioritize risk mitigation measures. This block captures a fundamental limit to the use of AI: algorithms can support the preparation of decisions, but should not replace the responsibility of state institutions for their adoption and implementation.

Risk control ensures the responsible use of AI in the public debt sector. It includes cybersecurity, model auditing, data quality control, explainability of results, documentation of methodological assumptions, forecast verification, maintaining the human-in-the-loop principle, and periodic assessment of AI solutions' compliance with debt policy objectives. This block prevents the transformation of digital tools into a closed or uncontrolled system of automated recommendations.

Debt sustainability monitoring and feedback complete the model and, at the same time, ensure its cyclicality. After management decisions are made, actual results should be compared with forecast values, and any identified deviations should be used to update assumptions, adjust models, and refine scenarios. Thus, the model is not static: it involves constant training of the system, accumulation of new data, and adaptation to changes in the macrofinancial environment.

The proposed conceptual model summarizes the research findings and provides the basis for further discussion of the conditions under which AI can be effectively used in the public debt management system. It combines the technological potential of intelligent systems with the requirements of institutional accountability, transparency, risk control, and strategic orientation of debt policy.

Discussion. The results obtained allow us to interpret artificial intelligence not as a separate technological element that is mechanically added to the public debt management system, but as a functional analytical layer that changes the logic of working with data, forecasts, risks, and management scenarios. The proposed sequence “data – AI analytics – scenario calculations – management decisions – risk control – debt sustainability monitoring” is consistent with the classical approach to debt management, according to which the main task of the state is to ensure financing needs at an acceptable cost-risk ratio in the medium and long term (International Monetary Fund & World Bank, 2014). At the same time, the results of this study expand the traditional vision, as they show that in the conditions of digital transformation, the effectiveness of debt policy depends not only on the choice of borrowing instruments, but also on the ability of the state to create an integrated information and analytical infrastructure for early identification of risks and support for strategic decisions.

A comparison of the proposed AI-based debt management system architecture with the approaches of international financial institutions demonstrates its methodological compatibility with modern standards of public debt management. In particular, the World Bank’s DeMPA methodology focuses on the quality of debt records, the functioning of debt management information systems, the availability of risk management procedures, auditing, reporting, and institutional coordination (World Bank, 2021). In this study, these elements are not denied but complemented by a digital dimension: high-quality debt data is considered not only as the basis for reporting but also as an input for forecasting, scenario analysis, anomaly detection, and the formulation of management warnings. Therefore, the proposed model can be considered as the next level of development of traditional debt management information systems, in which the information function is gradually transformed into an analytical and predictive one.

The results of the study are also consistent with the latest approaches to AI use in public financial management. OECD (2025a) considers AI as a tool that can be used in macro-fiscal forecasting, budget planning, budget execution monitoring, financial reporting, and interaction with participants in the fiscal process. IMF (2025) also emphasizes that AI technologies, particularly natural language processing tools, can help analyze large volumes of budget documentation, identify inconsistencies, and support the analytical work of public finance bodies. The results obtained in this article concretize these general approaches specifically for the area of public debt management: AI can be used not only to process documents or budget data, but also to assess the structure of the debt, future payments, refinancing risks, currency and interest rate sensitivity, as well as alternative debt policy trajectories.

It should be noted that the proposed classification of AI applications is consistent with empirical studies demonstrating the potential of machine learning to analyze debt sustainability and sovereign risks. In particular, Rafie (2024) shows that the use of ML approaches in the study of external debt sustainability allows us to better account for the complex interactions among macroeconomic factors, such as exchange rates, inflation, economic growth, and international reserves. Mutai et al. (2025), analyzing fiscal stress in eurozone countries, also highlight the limitations of static threshold approaches and the advantages of ML models for detecting nonlinear relationships in macrofiscal data. In this context, the results of this paper confirm that AI can be useful in those tasks where traditional models have limited ability to quickly account for multidimensional shocks and interdependencies.

At the same time, unlike studies that mainly focus on the predictive accuracy of ML models, this article focuses on the institutional integration of AI into the public debt management system. This is of fundamental importance, since the high accuracy of an individual model does not yet guarantee improved debt policy quality. For the practical use of AI results, clear model validation procedures, responsible decision-makers, rules for documenting assumptions, data quality control, and mechanisms for explaining results are necessary. That is why the proposed conceptual model includes not only analytical and technological blocks, but also institutional and governance layers. This approach allows the combination of the advantages of algorithmic analytics with the principles of accountability, transparency, and responsibility in public administration.

Interpreting the results in the context of AI risks also underscores the need for a cautious, gradual introduction of such technologies in public finance. The Financial Stability Board (2024) emphasizes that the use of AI in the financial sector can create new vulnerabilities related to cyber risks, dependence on external technology providers, model concentration, model governance challenges, and a lack of explainability in algorithms. BIS (2024) further emphasizes that central banks and financial authorities should simultaneously use the potential of AI and consider its impact on financial stability, macroeconomic processes, and operational security. The risk matrix developed in the article is consistent with these conclusions, but transfers them to the specific area of public debt, where a forecast error or incorrect interpretation of an algorithmic recommendation can have not only technological, but also budgetary, macro-financial and political consequences.

The results presented here suggest that the key condition for the effective use of AI in the public debt sector is not the maximum automation of processes, but the formation of a managed decision-support system. This distinguishes debt management from many applied financial processes in the private sector, where algorithms can be used for automated risk assessment, client segmentation, or operational monitoring. In the public debt sector, decisions regarding the structure of borrowings, maturities, currency composition, issuance volumes, and acceptable risk levels should remain institutionally responsible. Therefore, the human-in-the-loop principle in the proposed model is not an additional element but a basic condition for the legitimacy of AI use in the public finance system.

Another important result is the distinction between AI's capabilities and limitations. On the one hand, AI can speed up data processing, improve forecasting quality, ensure more regular risk monitoring, and expand the number of scenarios analyzed before making decisions. On the other hand, debt policy remains dependent on factors that cannot always be fully captured by an algorithmic model: geopolitical shocks, shifts in international support, investor behavior, security threats, institutional trust, and political decisions. That is why the study's results do not provide grounds for treating AI as a universal tool for solving debt sustainability problems. Its role is to improve the quality of the analytical basis for decisions, and not to eliminate the need for professional judgment, strategic planning, and institutional control.

Compared with existing approaches to the digital transformation of public finances, the proposed model is interdisciplinary. It combines an economic dimension related to the impact of public debt on macro-financial stability; a financial dimension covering the cost, structure, and risks of debt obligations; a managerial dimension related to the process of preparing and making decisions; and an IT dimension related to data, algorithms, digital platforms, and cybersecurity. It is this interdisciplinarity that reflects the modern nature of debt management, in which the quality of financial decisions increasingly depends on the quality of digital infrastructure, information exchange, and the analytical capacity of state institutions.

However, the results obtained have certain limitations that should be taken into account in further research. The proposed model is conceptual and does not provide empirical verification based on a specific set of debt, budget, or market data. The article does not assess the accuracy of individual ML algorithms for forecasting public debt, does not compare specific software solutions, and does not calculate the economic effect of implementing an AI-based debt management system. This means that the results should be considered a theoretical and methodological basis for the next stage of research, including the construction of applied models, data testing, the development of digital maturity indicators, and the assessment of institutions' readiness to use AI.

Thus, the debatable significance of the results obtained is that they combine two areas that are often considered separately in the scientific and analytical literature: traditional public debt management and digital transformation of public finances. The proposed model shows that integrating AI can increase the effectiveness of debt policy only if it is based on high-quality data, transparent algorithmic procedures, cybersecurity, model management, institutional responsibility, and human control over final decisions. This is the main difference between the proposed approach and the purely technological vision of AI: it is not about automating debt policy, but about creating a more mature, adaptive, and risk-oriented public debt management system in a digital environment.

Conclusion. The article substantiates that artificial intelligence can be an important tool for modernizing the public debt management system, but its role should not be to automate debt policy, but to strengthen the analytical capacity of state institutions. The main results of the study are to systematize the areas of application of AI in debt management, determine the information basis of the AI-based debt management system, group the opportunities and risks of its use, and form a conceptual model for integrating AI into the public debt management system.

The novelty of the proposed approach is that AI is considered as a functional analytical layer between data, forecasts, scenario calculations, and management decisions. This approach combines the traditional tasks of debt management – ensuring financing needs are met, controlling costs and risks, and maintaining debt sustainability – with the possibilities of digital transformation in public finances. At the same time, the effectiveness of such integration depends on data quality, cybersecurity, algorithm transparency, model management, institutional control, and preservation of the human-in-the-loop principle.

The practical significance of the results lies in their potential use in developing digital tools for the Ministry of Finance, debt offices, and other bodies responsible for the formulation and implementation of debt policy. The proposed model can be used to improve medium-term public debt management strategies, improve the quality of debt forecasting, strengthen monitoring of fiscal risks, and ensure transparency of public finances. Further research should focus on quantitative testing of AI tools for debt sustainability forecasting, assessing the readiness of state institutions to use AI, and developing ethical and legal standards for their application in public finance.

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