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Early detection of systemic financial risks using neural networks based on blockchain market signals

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Abstract. Traditional methods of analysis based on aggregated macroeconomic indicators are characterized by time lags and a limited ability to detect crises early. This necessitates the use of alternative sources of information and analysis tools that can provide early signals of financial instability. The **purpose of the study** is to substantiate a theoretical and methodological approach to the early detection of systemic financial risks using blockchain data and machine learning methods. The study used **methods** of generalization, analysis, comparison, and conceptual modeling, which allowed for the systematization of modern approaches to risk assessment, the identification of their limitations, and the justification of the feasibility of using innovative analytical tools. **Results**. The work structures systemic financial risks and identifies their key groups. The analysis results show that the most significant impact on financial stability is exerted by geopolitical and macroeconomic risks, which form the main sources of systemic instability in modern conditions. The analysis indicates the decisive influence of the state of economic activity, geopolitical threats, and inflationary processes on the formation of the most significant sources of systemic financial risks. It is substantiated that blockchain indicators, in particular, address activity, transaction volumes, exchange asset flows, and volatility indicators, allowing for the real-time reflection of market participants' behavioral reactions. A comparative analysis of traditional approaches and blockchain analytics has shown the advantages of using primary transactional data over aggregated macroeconomic indicators, due to greater objectivity, greater efficiency in obtaining information, and greater predictive potential. **Conclusions**. A conceptual model for early detection of systemic financial risks is proposed, integrating on-chain data and neural network algorithms to perform phased data processing, construct an integrated risk index, and classify it by levels, thereby providing a basis for informed management decisions. The practical significance of the results lies in their potential application by banks, regulators, and investors for monitoring financial stability, early detection of systemic risks, and crisis forecasting.

Keywords: systemic financial instability, on-chain data, behavioral signals, cryptoassets, machine learning, neural networks, risk forecasting, financial analytics.

Раннє виявлення системних фінансових ризиків нейромережами на основі ринкових сигналів блокчейну

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Анотація. Традиційні методи аналізу, що ґрунтуються на агрегованих макроекономічних показниках, характеризуються часовими лагами та обмеженою здатністю до раннього виявлення кризових явищ. Це зумовлює потребу у використанні альтернативних джерел інформації та аналітичних інструментів, здатних генерувати випереджальні сигнали фінансової нестабільності. **Метою дослідження** є обґрунтування теоретико-методичного підходу до раннього виявлення системних фінансових ризиків на основі використання блокчейн-даних та методів машинного навчання. Застосування **методів** узагальнення, аналізу, порівняння та концептуального моделювання дало змогу систематизувати сучасні підходи до оцінювання ризиків, визначити їхні обмеження й обґрунтувати доцільність упровадження інноваційних аналітичних інструментів. **Результати**. У роботі визначено й структуровано системні фінансові ризики. Встановлено, що найбільший вплив на фінансову стабільність мають геополітичні та макроекономічні чинники, які в сучасних умовах є основними джерелами системної нестабільності. Результати аналізу засвідчують визначальний вплив економічної активності, геополітичних загроз та інфляційних процесів на формування основних джерел системних фінансових ризиків. Обґрунтовано, що блокчейн-індикатори, зокрема активність адрес, обсяги транзакцій, потоки активів на біржі та показники волатильності, відображають поведінкові реакції учасників ринку в режимі реального часу. Порівняльний аналіз традиційних підходів та блокчейн-аналітики засвідчив переваги використання первинних транзакційних даних порівняно з агрегованими макроекономічними показниками завдяки вищій об'єктивності, оперативності отримання інформації та розширеному прогностичному потенціалу. **Висновки**. Розроблено концептуальну модель раннього виявлення системних фінансових ризиків. Завдяки інтеграції ончейн-даних та нейромережевих алгоритмів модель забезпечує поетапну обробку інформації, розрахунок інтегрального індексу ризику та його класифікацію для ухвалення обґрунтованих управлінських рішень. Практичне значення результатів полягає в можливості їхнього застосування банками, регуляторами та інвесторами для моніторингу фінансової стабільності, раннього виявлення системних ризиків та прогнозування криз.

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Ключові слова: системна фінансова нестабільність, ончейн-дані, поведінкові сигнали, криптоактиви, машинне навчання, нейромережі, прогнозування ризиків, фінансова аналітика.

Problem statement. The increasing volatility of financial markets, the strengthening of global imbalances and the development of digital financial instruments are changing the nature of systemic risks. The active spread of crypto-assets and decentralised finance is forming new risk transmission channels characterised by high speed, cross-border nature and significant dependence on the behaviour of market participants [1, p. 343]. This complicates ensuring financial stability and increases the requirements for analytical tools. Traditional approaches to assessing financial risks based on aggregated macroeconomic indicators have a limited ability to detect crises early, as they reflect already established trends [2]. The main problems are delays in indicator data, failure to account for behavioural factors, and the low adaptability of models to dynamic changes in the financial environment. In view of this, there is a need to adopt new approaches to risk analysis based on high-frequency data and modern information-processing methods to ensure early detection of potential threats to financial stability.

Analysis of recent research and publications. Modern scientific research demonstrates the active integration of artificial intelligence (AI) and machine learning methods into financial risk assessment, particularly in the context of digitalisation and the development of cryptocurrency markets. In particular, D. Konuk and H. Güvenir [3], as well as Z. Ke et al. [4], demonstrate that recurrent neural networks (LSTM, GRU, BiLSTM) provide effective forecasting of crisis phenomena and reversal signals using time series and multi-source data (on-chain metrics and behavioural factors). As M. Park et al. [5] and L. D'Amico et al. [6] demonstrate, the use of graph neural networks, structural-temporal models, and quantum-inspired approaches provides effective detection of anomalies and fraudulent transactions in blockchain networks, thereby enabling early risk prevention. At the same time, in the works of Z. Luo et al. [7, p. 5] and Z. Babaei et al. [8, p. 3], it was found that machine learning and hybrid models achieve higher accuracy in predicting systemic financial risks than traditional econometric approaches. However, reliance on data quality and the complexity of interpretation remain significant limitations to their practical application in the analysis and forecasting of financial risks. Similar conclusions are confirmed in the study by T. Su et al., which shows that integrating LSTM, Transformer, and wavelet analysis increases anomaly detection accuracy but complicates computational processes [9, p. 70]. A separate area of research concerns the use of AI in decentralised financial systems. For example, S. Davor substantiates the effectiveness of integrating on-chain data, smart contracts, and behavioural signals for predicting risks in DeFi [10, p. 316], while O. Brechko and V. Schuchmann emphasise the importance of algorithmic adaptability and the integration of big data to minimise crypto market volatility [11, p. 46]. Researchers R. Loik [12] and O. Babych [2] emphasise that the implementation of blockchain technologies increases the transparency, security and efficiency of financial transactions, but is accompanied by regulatory restrictions, increased costs and the emergence of new types of risks that require systematic consideration. At the same time, V. Moskalenko and colleagues emphasise the limitations of traditional time-series models and the feasibility of hybrid approaches using machine learning to improve forecasting accuracy in conditions of high market volatility [13, p. 43]. An important aspect is the technological infrastructure required to implement such models. As noted by Y. Bershchanskyi and colleagues [14, p. 152], O. Lega and A. Makarchuk [15, p. 106], the use of containerised AI systems and ensemble models provides high accuracy, stability and scalability of data processing – the determining factors of effective financial monitoring.

The generalisation of scientific approaches demonstrates the feasibility of combining blockchain analytics and neural network methods as a basis for creating adaptive systems for early risk prevention in finance.

Highlighting previously unresolved parts of the general problem. Despite significant scientific achievements in applying machine learning to assess financial risks, the issues of timely detection of systemic risks at their early stages of formation, integration of behavioural factors into the analysis process, and comprehensive use of on-chain data as leading indicators of financial instability remain unresolved. Existing approaches are mainly focused on analysing historical or aggregated data, which limits the ability to respond rapidly, while the potential of blockchain data for the formation of early warning systems remains underexploited. In addition, there are no generalised approaches to integrating neural network models with on-chain analytics to form a holistic assessment of financial risk.

Formulation of the article's goals (task statement). The purpose of the study is to substantiate an approach to early detection of systemic financial risks by using on-chain blockchain data as early signals, along with neural network models for analysis, forecasting, and integrated assessment.

Presentation of the main material of the study. The instability of financial markets, the intensification of geopolitical shocks, and the development of digital financial instruments make the timely detection of systemic financial risks relevant. Their feature is the ability to quickly spread between segments of the financial system, transforming local disruptions into large-scale crisis processes. Systemic financial risk is defined as the probability of disruption to the stable functioning of the financial system due to interrelated factors that cause liquidity loss, reduced confidence in financial institutions, and the emergence of chain effects. Unlike individual risks, it is cumulative and arises from a network of relationships among market participants, institutions, and financial instruments [2].

The structuring of systemic risks allows us to distinguish several interrelated groups. Macroeconomic risks include fluctuations in economic activity, inflation, currency instability and changes in monetary policy. Financial risks include liquidity, credit losses, deterioration in asset quality, and bankruptcy risk. Institutional risks are shaped by the quality of the regulatory environment, the effectiveness of the judicial system, and the level of protection of investor rights. External risks reflect the impact of global shocks, changes in world prices and geopolitical factors. A separate group comprises technological and behavioural risks arising from cyber threats, digital financial instruments, and mass market reactions [2].

The digitalisation of the financial system significantly changes the mechanisms of risk formation and spread. The use of financial technologies, big data, and AI algorithms increases the speed of information processing and expands analytical capabilities. At the same time, the development of crypto-assets and decentralised finance creates new sources of instability, including high volatility, limited regulation, and significant influence from behavioural factors. Such risks are characterised by a high rate of spread, a cross-border nature, and the complexity of forecasting [11, p. 50]. This complicates their timely identification based on traditional statistical indicators and requires the use of analytical approaches that allow assessing the structure of threats and determining their priority. For this, it is advisable to turn to empirical assessments of systemic financial risks, in particular data from the National Bank of Ukraine [17], which reflect the perceptions of financial sector participants and provide their analytical interpretations (table 1).

Table 1

Systemic financial risks in Ukraine according to the NBU assessment and their analytical interpretation, 2025

Risk factor	High impact, %*	Low impact, %*	Risk balance**	Threat level	Nature of impact
War and geopolitical risks	59	6	+53	Critical	Systemic
Economic activity	47	12	+35	High	Macroeconomic
Inflation	47	15	+32	High	Macroeconomic
World prices	38	18	+20	Elevated	External
Public policy	30	22	+8	Medium	Macroeconomic
Cyber threats	29	27	+2	Medium	Technological
Exchange rate	30	37	-7	Moderate	Foreign
Access to financing	21	35	-14	Moderate	Liquidity
Judicial system	15	32	-17	Moderate	Institutional

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Risk factor	High impact, %*	Low impact, %*	Risk balance**	Threat level	Nature of impact
Human capital	12	29	-17	Moderate	Structural
Corruption	18	44	-26	Medium	Institutional
Investment	8	36	-28	Medium	Investment
Bankruptcies	21	49	-28	Medium	Financial
Pandemics	6	38	-32	Low	External
Investor Protection	12	50	-38	Low	Legal
Taxation	9	50	-41	Low	Fiscal
Climate Risks	9	56	-47	Low	ESG
Asset Value	6	56	-50	Low	Market
Virtual Assets	3	64	-61	Low	New

Note: *The indicators «High Impact, %» and «Low Impact, %» reflect the share of financial sector respondents who assess the respective factor as having a high or low level of impact on financial stability.

**The risk balance is calculated as the difference between the proportion of high and low scores and characterizes the prevalence of risk perception: a positive value indicates a prevalence of high-risk scores; a negative value indicates a prevalence of low scores.

Source: compiled by the author based on [17]

The above indicators confirm the concentration of systemic risks in the macroeconomic and geopolitical spheres. The decisive role is played by military and geopolitical factors, which have a systemic nature and shape the general configuration of threats to Ukraine's financial sector. The group of increased impact also includes risks associated with the dynamics of economic activity and inflationary processes, which directly affect the macro-financial balance. At the same time, external factors, particularly fluctuations in global prices, increase the national economy's dependence on the global situation. The average level of threat is inherent in the risks associated with state policy and cyber threats, indicating a gradual increase in the role of institutional and technological factors in destabilising the financial system. Some risks are latent: despite their low short-term manifestation intensity, their potential destructive impact remains significant. This group includes restrictions on access to finance, shortcomings in the functioning of the judicial system and a decline in the quality of human capital. The least pronounced is the level of identification of new structural factors, particularly climate and those related to virtual assets, indicating their underestimation despite potentially significant long-term consequences. Thus, the predominance of geopolitical and macroeconomic threats is combined with a gradual strengthening

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of the role of technological and new sources, reflecting the transformation of sources of financial instability and justifying the need for early-detection tools. Traditional approaches based on aggregate statistics mostly record already realised risks, which limits their predictive potential. In this context, real-time alternative data sources that reflect market participants' behaviour are particularly important. One of these is blockchain, which provides access to on-chain data - information about transactions, user activity and the movement of digital assets. Unlike traditional indicators, these data are characterised by high transparency, accessibility, and frequent updates, which allow for capturing changes in market sentiment at early stages [12; 18].

On-chain indicators reflect not only quantitative market parameters but also behavioural reactions of investors, in particular, asset accumulation, mass sales, increased activity, or a panic mood. This enables identifying potential risks before they manifest in macroeconomic indicators, effectively turning the blockchain into an advanced diagnostic system for financial instability [19]. To systematise such signals and determine their analytical value, it is advisable to classify the main on-chain indicators of financial risks (table 2).

Table 2

On-chain blockchain indicators as early signals of systemic financial risks

On-chain indicator	Economic content of the indicator	Behavioral interpretation	Type of financial risk	Signal interpretation
Active addresses	Level of network activity of users	Increasing interest or panic reactions	Behavioral	A sharp increase is a sign of market overheating
Transaction volume	Intensity of digital asset movement	Activation of operating activity	Market	High volumes are associated with an increase in volatility
Exchange inflow	Volume of assets entering the exchange	Tendency to sell	Market liquidity risk	An increase is a potential pressure on prices
Exchange outflow	Volume of assets being withdrawn from exchanges	Accumulation and holding of assets	Market liquidity risk	Growth is a signal of stabilisation
Whale transactions	Large transactions by large players	Influence of large investors on the market	Manipulative	Concentration of transactions – risk of sudden changes
MVRV	Ratio of market to	Level of	Bubbly	Value >1 – market

On-chain indicator	Economic content of the indicator	Behavioral interpretation	Type of financial risk	Signal interpretation
ratio	realised value	unrealised profit		overheating
Volatility	Amplitude of price fluctuations	Instability of expectations	Market	Rapid growth – increased risk
Stablecoin supply	Volume of liquid digital assets	Willingness to invest	Market liquidity risk	Increase – potential demand

Source: compiled from [19]

An analytical interpretation of on-chain indicators demonstrates their ability to reflect market participants' behavioural reactions in real time. In particular, the growth of user activity and transaction volumes signals an overheating phase, while changes in flows on the exchange (inflow / outflow) reflect a change in investment strategies – from selling to accumulating. At the same time, large transactions («whale transactions») are a trigger for sharp market changes, and the MVRV indicator allows you to identify the formation of price bubbles. Thus, on-chain data combines economic and behavioural content, which facilitates the interpretation of market processes through investor reactions – panic, accumulation or speculative activity. This contributes to the formation of leading signals that precede changes reflected in traditional macro-financial indicators, confirming the feasibility of using blockchain as a tool for early detection of financial risks [19]. At the same time, to substantiate the advantages of such an approach, it is advisable to compare it with traditional risk assessment methods based on macroeconomic and technical indicators (table 3).

Table 3

Comparative characteristics of approaches to assessing systemic financial risks

Assessment criterion	Traditional financial indicators	On-chain blockchain data	Identified advantages
Data source	Aggregate macro and financial indicators	Primary transaction data	The use of on-chain data provides a more accurate reflection of market processes due to the primary nature of the information
Time characteristic	Lag (with a delay)	Real-time	On-chain data allows for proactive analysis, unlike delayed macroeconomic indicators

Assessment criterion	Traditional financial indicators	On-chain blockchain data	Identified advantages
Level of objectivity	Depends on the processing method	High level of transparency	An on-chain approach reduces the risk of information distortions compared to aggregated data
Consideration of behavioural factors	Limited or absent	Integrated into indicators	On-chain data allows for behavioural reactions of market participants that are not reflected in traditional approaches
Predictive potential	Limited	Expanded	On-chain indicators generate early risk signals, which increase forecasting accuracy
Adaptability to changes	Low	High	On-chain analysis provides a more efficient response to changes in the financial environment
Functional purpose	Assessment of the current state	Early detection of risks	The use of on-chain data contributes to the transition from descriptive analysis to early warning systems

Source: compiled by the author

Thus, traditional indicators primarily record already established trends, whereas on-chain data enables the identification of changes at early stages of development. The use of primary transactional data increases the accuracy and objectivity of the assessment, and the integration of behavioural factors expands the range of interpretations of market processes. This forms the basis for the transition from reactive analysis to preventive risk management.

Given the increasing speed of financial flows and the complexity of the market structure, there is a need for tools that can not only record changes but also predict their development based on large volumes of heterogeneous data. This becomes especially relevant in the context of the digitalisation of the financial system, where the volume of information is growing, and the time lag between the emergence of a signal and its manifestation in traditional indicators is decreasing.

Blockchain data serves as the basis for a system to prevent financial risks early. At the same time, the effectiveness of their use mainly depends on the availability of analytical tools capable of detecting hidden patterns, processing nonlinear dependencies, and generating predictive estimates. These tasks are solved using machine learning methods, which provide a new level of financial risk analysis. The use of machine learning algorithms in the financial sector enables the processing of large datasets, the identification of complex relationships between indicators, and the development of predictive risk models. Unlike classical econometric approaches, modern neural network models can adapt to environmental changes, account for time dynamics, and integrate behavioural factors, which is critically important for the analysis of on-chain data [13, p. 48; 15, p. 111]. A feature of neural networks in financial research is their ability to handle high-frequency data and detect early signals of instability, thereby increasing the accuracy of forecasting crisis phenomena. This creates the possibility of integrating blockchain data and machine learning algorithms into a single monitoring system focused on early detection of systemic financial risks. To systematise modern approaches to machine learning in financial analytics, it is advisable to consider the main methods and their functionalities (table 4).

Table 4

Machine learning methods for early detection of systemic financial risks

Machine learning method	Task type	Scope of application	Advantages	Limitations
LSTM (Long Short-Term Memory)	Time series analysis	Crisis forecasting	Allows for taking into account long-term dependencies and dynamics	High computational complexity
GRU (Gated Recurrent Unit)	Time series analysis	Online risk monitoring	High data processing speed, fewer parameters	Lower accuracy in complex models
Random Forest	Classification	Basic risk assessment	Noise-resistant, high stability	No consideration of time dependence
XGBoost	Classification / regression	Quantitative assessment of the risk level	High accuracy and efficiency when processing big data	Risk of overfitting, difficulty of tuning
SVM (Support Vector Machine)	Classification	Crisis detection	High accuracy when processing small samples	Difficulty of interpretation and scaling
Logistic Regression	Binary classification	Basic model comparison	Interpretability of results	Limited accuracy for nonlinear dependencies

Source: built according to [1; 2; 4; 7]

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Analysis of machine learning methods shows that their choice is determined by the nature of the data and the analytical tasks set. Recurrent neural networks (LSTM, GRU) are the most effective for processing time series and can account for dynamic changes, which is critically important for analysing on-chain data. Ensemble methods (Random Forest, XGBoost) provide high accuracy in classification and risk assessment but are limited in their ability to capture temporal dependencies. Classical approaches, in particular logistic regression, are appropriate for basic comparison and interpretation of results. Thus, the use of machine learning methods enables the effective processing of complex, high-frequency, and multidimensional data, laying the foundation for building models to detect systemic financial risks early. At the same time, the effectiveness of such approaches requires their integration into a holistic analytical system that will ensure the transition from data processing to the formation of management decisions.

The feasibility of developing a conceptual model for early detection of systemic financial risks that combines on-chain analytics and neural network methods is substantiated (table 5).

Table 5

Model for early detection of systemic financial risks

Stage			
Implementation tools	Input data	Analytical result	Management value
Monitoring market signals			
Blockchain analytics, API, data-streaming	On-chain indicators (address activity, transaction volumes, asset flows between wallets and exchanges)	Initial signals of changes in market behaviour	Early detection of potential market shifts
Data preprocessing			
Cleaning, normalisation, aggregation	Initial blockchain transaction data	Prepared and structured data	Improving the quality and objectivity of analysis
Analytical processing			
Neural networks (LSTM, GRU,	High-frequency on-chain data array	Risk probability forecast	Quantitative assessment of the level of financial

Stage			
Implementation tools	Input data	Analytical result	Management value
XGBoost)			risk
Assessment risk			
Integral index, scoring models	Aggregate risk indicators	Integral risk level indicator	Ranking of threats by degree of impact
Interpretation of results			
Analytical rules, threshold values	Model results	Risk level classification (low / medium / high)	Support for management decision-making
Management response			
Risk management, scenario analysis	Risk level assessments	Response recommendations	Risk minimisation and ensuring financial stability

Source: compiled by the author

The proposed approach uses blockchain data as a source of leading signals, which are then processed with machine learning algorithms to assess risk levels. Structurally, the model consists of three main blocks. The input block serves as the research information base and contains on-chain indicators that reflect the activity of market participants, the movement of digital assets, and changes in market sentiment. The analytical block provides data processing, cleaning, normalisation, and analysis using neural network models that can detect hidden patterns and predict the development of risks. The final block involves the formation of an integral risk indicator and its classification by levels, which provides the basis for management decisions. The proposed model is based on a phased implementation algorithm that ensures systematic data processing and enhances the validity of analysis results. Its application allows not only detecting already formed risks but also identifying early manifestations of their formation, thereby increasing the efficiency of financial stability management.

The practical significance of the model lies in its potential application by banks, regulators, and investors to monitor financial stability, manage liquidity, and prevent crisis phenomena. The use of an integral risk index and automated analysis algorithms lay the groundwork for transitioning to an early warning system, enabling timely responses to potential threats and reducing their negative impact on the financial system.

Conclusions. According to the study's results, systemic financial risks are formed by a complex of interrelated factors, among which geopolitical and macroeconomic factors play a decisive role. This determines the level of financial instability and the direction of its development. At the same time, it is proven that traditional approaches to risk assessment have limited predictive power, as they mainly capture established trends and do not detect early signals of their occurrence in a timely manner.

It is substantiated that the use of on-chain blockchain indicators enables the generation of advanced signals on financial risks by reflecting market participants' behavioural reactions in real time. This provides increased objectivity and analysis efficiency, and also expands the possibilities for interpreting market processes. The feasibility of using machine learning methods for processing high-frequency financial data has been demonstrated, enabling the consideration of nonlinear dependencies and improving the accuracy of assessing and forecasting systemic financial risks. A model for early detection of systemic financial risks has been proposed that, by combining blockchain analytics tools and machine learning methods, produces an integrated assessment of risk level and subsequent classification.

The practical significance of the proposed approach lies in its potential to enhance the effectiveness of monitoring financial stability, justify management decisions, and minimise financial sector risks. Prospects for further research include developing quantitative models to assess systemic financial risks using real on-chain data and building adaptive risk management systems in the context of the digital transformation of the financial environment.

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