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Neural network forecasting of systemic financial risk based on blockchain market signals

Diana Samodina,

Master of Finance, Founder and Executive Director, Center for Applied Economic Innovation and Research, Burbank, CA 91502, USA,

https://orcid.org/0009-0000-0888-7927

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Abstract. The modern financial system operates amid digitalization and the growing integration of blockchain infrastructure into global market processes. The expansion of digital assets and the increasing speed of financial transactions generate new sources of systemic instability that are not fully captured by traditional macro-financial indicators. This necessitates the application of analytical tools that account for nonlinearity, temporal dynamics, and the networked nature of financial processes. The **study aims** to substantiate the feasibility of using structured blockchain signals to model the dynamics of systemic financial risk and to test a neural network approach to its forecasting. **Methods**. The methodological framework integrates economic-statistical analysis of blockchain metrics with deep learning techniques. It is planned to systematize blockchain signals by functional group based on their economic content, and to develop a set of relevant predictors for further algorithmic analysis. Modeling is based on a recurrent neural network that accounts for the temporal structure of the data and lag dependencies. The model design focuses on developing an integrated indicator of systemic financial risk that accounts for nonlinear changes. **Results**. The findings reveal a statistically significant relationship between classified blockchain signals and periods of increased market turbulence. The proposed neural network model enables the timely identification of systemic financial risk escalation and reduces the forecasting lag compared to conventional approaches. Empirical validation confirms the model's ability to capture nonlinear dependencies and the cumulative effects of market signals. **Conclusions**. The study substantiates the relevance of blockchain signals as an informational basis for forecasting systemic financial risk. The proposed approach expands the analytical toolkit for financial stability monitoring and provides a foundation for developing adaptive early warning systems. The results may be applied in risk management practice, macro-financial analysis, and regulatory supervision.

Keywords: financial instability, digital assets, deep learning, risk index, early warning, volatility.

Нейромережеве прогнозування системних фінансових ризиків на основі блокчейн-сигналів ринку

Самодіна Діана,

магістр фінансів, засновник та керівник дослідницького проєкту, Center for Applied Economic Innovation and Research, м. Бербанк, Каліфорнія 91502, США, https://orcid.org/0009-0000-0888-7927

Анотація. Сучасна фінансова система функціонує в умовах цифровізації та посиленої інтеграції блокчейн-інфраструктури в глобальні ринкові процеси. Поширення цифрових активів і зростання швидкості фінансових транзакцій формують нові джерела системної нестабільності, які традиційні

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макрофінансові індикатори відображають не повною мірою. Це зумовлює потребу у впровадженні інструментів аналізу, здатних ураховувати нелінійність, часову динаміку та мережевий характер фінансових процесів. **Метою дослідження** є обґрунтування можливості використання структурованих блокчейн-сигналів для моделювання динаміки системного фінансового ризику та апробація нейромережевого підходу до його прогнозування. **Методологічну основу роботи** становить інтеграція економіко-статистичного аналізу блокчейн-метрик і методів глибинного навчання. Передбачено систематизацію блокчейн-сигналів за функціональними групами відповідно до їх економічного змісту, а також формування набору релевантних предикторів для подальшого алгоритмічного аналізу. Моделювання здійснено на основі рекурентної нейронної мережі та взято до уваги часову структуру даних і лагових залежностей. Конструкція моделі орієнтована на створення інтегрального індикатора системного фінансового ризику з урахуванням нелінійної взаємодії змінних. **Результати.** Установлено, що класифіковані блокчейн-сигнали демонструють статистично значущий зв’язок із фазами підвищеної ринкової турбулентності. Побудована нейромережева модель забезпечує своєчасну ідентифікацію періодів зростання системного фінансового ризику та зменшує лаг прогнозування порівняно з традиційними підходами. Емпірична перевірка підтвердила здатність моделі враховувати нелінійні залежності та кумулятивний ефект сигналів. **Висновки.** Доведено доцільність застосування блокчейн-сигналів як інформаційної бази для прогнозування системного фінансового ризику. Запропонований підхід розширює інструментарій моніторингу фінансової стабільності та формує підґрунтя для розроблення адаптивних систем раннього попередження. Отримані результати можуть бути використані в практиці ризик-менеджменту, макрофінансового аналізу та регуляторного нагляду.

Ключові слова: фінансова нестабільність, цифрові активи, глибинне навчання, індекс ризику, раннє попередження, волатильність.

Statement of the problem. The modern financial system operates amid digital transformation, where a significant portion of market activity occurs in decentralized environments. The growing role of digital assets and the integration of blockchain infrastructure into global financial flows create new sources of systemic risk that traditional macro-financial indicators may not always reflect.

Existing financial stability monitoring tools are mostly based on aggregated statistical indicators characterized by time lags and limited sensitivity to behavioral changes of market participants. At the same time, the blockchain environment generates deterministic, open data on transaction activity, capital concentration, and liquidity that can serve as early warning signals of systemic instability.

Therefore, the problem arises of integrating high-frequency blockchain signals into the systemic financial risk forecasting model using tools that account for nonlinearity and the time dynamics of processes. Solving this problem is important for the development of adaptive early warning systems, the improvement of risk management, and the efficiency of macro-financial regulation**.**

Analysis of recent research and publications. The analysis of modern scientific sources confirms the intensification of research into the application of artificial intelligence and neural network models for forecasting financial indicators, risk management, and the analysis of digital markets. At the same time, integrating blockchain signals into the systemic financial risk forecasting system remains a nascent area.

Thus, L. Liutiuk, E. Hnatchuk, and O. Ponchovna [1] justify the feasibility of using neural networks for forecasting financial markets, emphasizing the ability of models to account for nonlinear dependencies and the temporal dynamics of data. Their conclusions provide a methodological basis for constructing neural network architectures in financial analytics. Scientists T. O. Semenenko and V. M. Domrachev [2] study the forecasting of the dynamics of macroeconomic indicators, focusing on methods of economic and mathematical modeling and time-series analysis. The presented approach is important for forming the macro-level component of systemic financial risk assessment and for accounting for the influence of general economic factors. The authors H. V. Maziutynets and M. M. Sharkadi [3] propose a multi-level neural network model for assessing a company's financial security, demonstrating the potential of deep architectures for risk assessment. Their results confirm the effectiveness of multilayer structures for complex economic systems.

A systematic review of the use of artificial intelligence systems in financial index forecasting tasks is carried out by M. Ya. Kushnir and K. A. Tokareva [4]. The authors summarized modern machine learning approaches and their application possibilities. The work is important for establishing a theoretical and methodological basis for the application of algorithmic models in financial forecasting. Scientists S. H. Osyka and K. B. Kulikov [5] analyze the functioning of the Aladdin platform as a risk management tool, providing a practical example of the integration of algorithmic systems into the financial infrastructure.

Researcher B. Bebeshko [6], in his article, systematizes methods for forecasting the market for digital cryptocurrencies, emphasizing the importance of machine learning algorithms for analyzing highly volatile assets. And V. Klymenko [7] examines the use of artificial intelligence tools to improve the accuracy of forecasting economic indicators in digital entrepreneurship, thereby expanding understanding of the adaptability of models to unstable environments.

The effectiveness of artificial intelligence in forecasting financial indicators is substantiated by V. Farion, A. Homotiuk, R. Nazar, and S. Turchyn [8], who emphasize the processing of large datasets. V. V. Pryimuk [9] analyzes the implementation of artificial intelligence technologies in the enterprise's financial activities, defining the organizational, technological, and analytical aspects of the digital transformation of financial management. The author emphasizes the role of automated risk assessment systems and management decision support. Scientists M. Basheri and M. Ragab [10] propose a robust approach to market share forecasting using fuzzy sets and hybrid methods, which increases the range of financial analytics tools.

Researching the digital transformation of the financial sector, scientists A. Al-Ashmori, G. Thangarasu, P. D. D. Dominic, and A.-B. A. Al-Mekhlafi [11] developed a readiness model and identified influencing factors on the implementation of blockchain technologies in the software sector. The obtained results provide an institutional and organizational basis for integrating blockchain solutions into the financial infrastructure and risk analysis systems. In their review, A. W. Li and G. S. Bastos [12] study stock market forecasting using deep learning and technical analysis, generalizing model architectures (LSTM, CNN, and hybrid approaches) and determining their effectiveness in financial forecasting tasks.

K. Sako, B. N. Mpinda, and P. C. Rodrigues [13] evaluate the use of neural networks for forecasting financial time series, emphasizing the role of nonlinear modeling and the adaptability of algorithms in handling volatile market data. T. B. Shahi, A. Shrestha, A. Neupane, and W. Guo perform a comparative analysis of deep learning models for stock price forecasting [14], demonstrating the advantages of LSTM, GRU, and other architectures for short- and medium-term forecasting. W. Sulandari et al. [15] develop hybrid forecasting models based on Singular Spectrum Analysis (SSA) that combine time series decomposition with modern forecasting algorithms, increasing the accuracy of financial forecasting in conditions of complex data dynamics.

Therefore, the review of scientific sources shows the active development of neural network approaches in financial forecasting and risk management, particularly in the field of digital assets.

Highlighting previously unresolved parts of the overall problem. Despite active research in financial analytics and deep learning, several issues remain understudied. In particular, there is no agreed classification of blockchain signals as a systematic group of predictors of financial instability. In addition, in most works, individual metrics are presented in isolation, without forming a coherent set of indicators, which limits the scope of comprehensive risk analysis. There is an urgent need for models that integrate the temporal dynamics of blockchain data with predictive assessment of systemic financial risk. Some works focus only on forecasting price fluctuations or volatility, ignoring the systemic dimension of risk and its potential cumulative effects. Little studied is the issue of empirically verifying such models during crisis phases, when nonlinear interrelationships among signals and their cumulative influence become most critical. It is also necessary to define effective criteria for comparing forecasts with actual data for various scenarios of market turbulence. The identification of these gaps underscores the need for further research to develop methodologically consistent and empirically validated models for forecasting systemic financial risk. The specified unresolved issues form the basis for formulating the goals and objectives of this work, revealing the directions of its scientific contribution.

Formulation of the article goals (task statement). The central purpose of the article is to address unresolved challenges in classification, modeling, and empirical validation by developing and testing a neural network model to predict systemic financial risk using classified blockchain market signals.

To achieve this, the following concrete goals are pursued:

1. To identify and classify blockchain market signals as potential predictors of systemic financial risk, with the determination of their economic content and functional groups.

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2. Develop a neural network model for forecasting the integral index of systemic financial risk, which takes into account time dynamics and nonlinear dependencies between signals.

3. Carry out empirical validation of the model and evaluate its prognostic effectiveness.

Presentation of the main research material. The modern financial system is characterized by increasing nonlinearity of processes, increasing interdependencies between market segments, and increasing speed of propagation of crisis impulses. In these conditions, traditional approaches to assessing systemic risk gradually lose prognostic sensitivity, which necessitates the integration of machine learning methods into financial analytics [1, p. 179; 11; 13]. In light of the mentioned transformations, it is advisable to use neural network models to detect hidden nonlinear dependencies and early indicators of financial instability.

The integration of deep learning algorithms for the study of time series and multidimensional financial indicators generated in the digital environment is particularly important today. The development of blockchain technologies has expanded the analytical information base by defining a new class of open data on transaction activity, asset ownership structures, and liquidity flows. It is these characteristics that enable capturing behavioral and structural changes in the market in real time, thereby laying the groundwork for building models to early warn of crisis phases using recurrent neural networks.

At the same time, the problem of systematizing blockchain signals as predictors of financial risk remains insufficiently formalized. In existing studies, attention is mostly focused on forecasting individual indicators of volatility or price trends, whereas an integrated risk assessment requires a structured approach to selecting variables and their economic interpretation.

Therefore, the task of creating a conceptually ordered system of blockchain signals to serve as a methodological basis for further neural network modeling of the systemic financial risk index arises (table 1).

Table 1

Classification of blockchain signals as predictors of systemic financial risk

A group of signals			
Indicator	**Economic interpretation**	**Potential impact on systemic risk**	**Analytical recommendations**
Transaction activity			
Volume of transactions	It shows the dynamics of the total volume of transactions in the network and characterizes the intensity of movement of digital capital between market participants	A sharp increase in the total volume of transactions in a short time interval indicates the activation of speculative or panic behavior in the market and precedes the phase of increased volatility	RNN/LSTM models should be used to detect anomalous changes and structural breaks in transaction activity time series
Network streams			
Net Flow to exchanges	The indicator reproduces the net inflow or outflow of assets to centralized exchanges and reflects the change in liquidation intentions of investors	A significant increase in the net inflow of assets on the exchange may signal preparations for a massive sell-off and an increase in short-term price pressure	It is recommended to model the impact of this indicator on volatility using hybrid SSA-neural network algorithms
Concentration of capital			
Index of «whales»	Determines the degree of concentration of assets in large wallets and outlines the level of structural asymmetry of capital distribution	An increase in the share of assets concentrated in large owners increases the systemic vulnerability of the market in the event of their synchronized exit from positions	It is advisable to integrate the indicator into multi-level neural network models to increase the accuracy of system risk forecasting
Volatility			
On-chain volatility	Reflects the variability of transaction activity and the amplitude of fluctuations of network indicators in time dynamics	The formation of abnormally high peaks of volatility may precede the transition of the market to a phase of instability or crisis escalation	It is advisable to use CNN-BiLSTM models to detect hidden patterns in multidimensional time series
Liquidity			

A group of signals			
Indicator	**Economic interpretation**	**Potential impact on systemic risk**	**Analytical recommendations**
Stablecoin Supply Ratio	It characterizes the ratio of the volume of stable liquid assets to the total market capitalization and shows the potential for rapid redistribution of capital	A decrease in the share of liquid assets can limit the market's ability to absorb shocks and increase the risk of cascading sales	It is recommended to integrate the indicator into the forecasting model of market shocks using SSA-component analysis

Source: compiled by the author based on [4, p. 108–117; 14; 15, p. 2178]

The proposed classification is based on a risk-oriented approach to analyzing digital assets and meets modern methodological requirements for forecasting financial turbulence using deep learning models. At the same time, the selection of functional groups (transaction activity, network flows, capital concentration, volatility, liquidity) enables the integration of behavioral, structural, and liquidity characteristics of the crypto market into a single system of variables. This minimizes analysis fragmentation and ensures a transition from descriptive monitoring of indicators to their systematic interpretation as early signals of financial destabilization.

The methodological value of the proposed classification lies in constructing a structured input space for further neural network modeling, particularly for architectures focused on detecting nonlinear dependencies and cascading effects in financial systems. The grouping of indicators by economic meaning reduces information noise, increases the model's interpretability, and helps identify the phases of systemic risk escalation.

Therefore, the formed classification of blockchain signals reflects a structured feature space that meets the requirements of multi-level neural network modeling of financial security. As shown earlier [3, p. 175], the effectiveness of forecasting increases significantly with prior economic interpretation and prioritization of input variables. At the same time, systematic reviews in computational finance emphasize the feasibility of using recurrent architectures for working with financial time series, where lag dependencies and nonlinear relationships between indicators play a central role [11].

Therefore, the transition from the classification model (table 1) to the formalized neural network architecture is not only a logical continuation of the research but also a methodologically justified step toward integrating structured blockchain metrics into the predictive algorithm for assessing systemic financial risk.

Since systemic financial risk is characterized by nonlinearity, latent dependencies, and time lags between signals and their macro-financial consequences, the use of recurrent neural networks, in particular the Long Short-Term Memory (LSTM) architecture, is methodologically justified for its assessment (fig. 1).

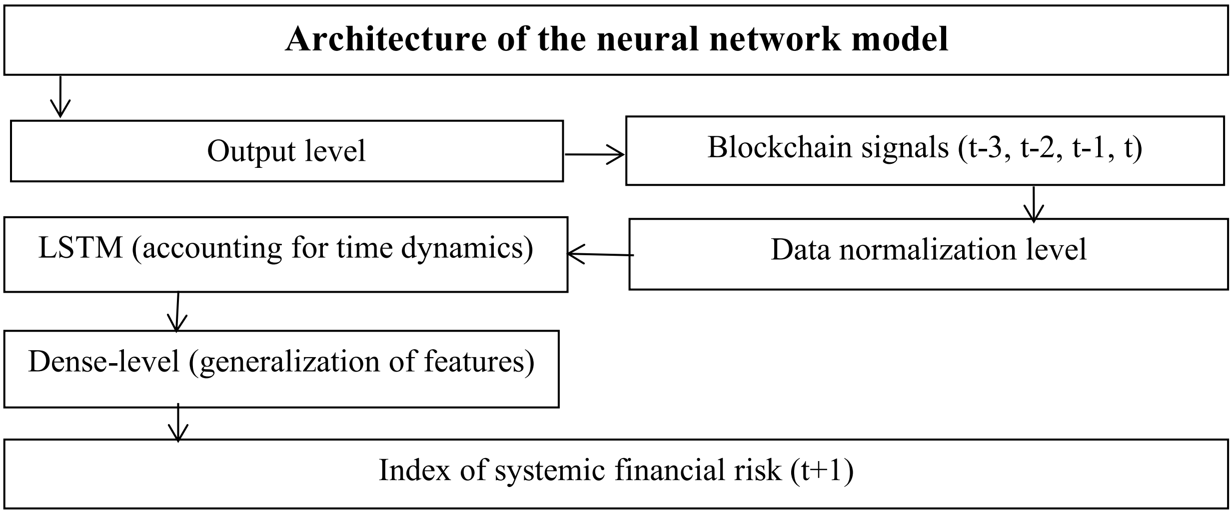

Fig. 1. Architecture of the neural network prediction model

Source: compiled by the author based on [3, p. 176; 11; 13]

The architecture of the neural network model reflects the sequential transformation of multidimensional blockchain signals into an integrated index of systemic financial risk, capturing the time dynamics of the market, and its structural logic aligns with modern approaches to multi-level neural network modeling of financial security and risk forecasting. The level of data normalization provides

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large-scale consistency in input variables and reduces data variability, thereby increasing the stability of model learning. The use of LSTM enables the consideration of nonlinear time dependencies, the cumulative effect of signals, and lag relationships between market indicators, which is fundamentally important for the identification of pre-crisis phases. Dense-level summarizes hidden signals and forms a latent representation of the system's risk state.

Therefore, the proposed architecture ensures methodological consistency between the nature of the phenomenon under study – a dynamic, nonlinear and network-connected financial system – and the tools for its analysis. Fig. 1 demonstrates not only the technical structure of the model, but also the conceptual transition from descriptive analysis of blockchain metrics to formalized algorithmic forecasting of systemic financial risk.

At the same time, the neural network architecture must be empirically confirmed for its prognostic adequacy. In modern studies of financial modeling, special attention is paid not only to the accuracy of prediction, but also to the stability of the model in conditions of structural shifts and market turbulence [9, p. 183]. Given the non-linear nature of systemic risk and the possibility of cascading effects, it is fundamentally important to test the neural network's ability to detect pre-crisis signals in a timely manner, rather than merely reproducing the indicator's average dynamics. That is why it is important to evaluate the accuracy, sensitivity and predictive ability of the developed model.

Empirical verification is the defining stage of prognostic research, as it allows assessing not only the statistical validity of the model but also its practical relevance for monitoring financial stability. In the context of increased volatility in digital markets, it is critical to consider not only average error rates but also the model's ability to timely capture turning points in risk dynamics, particularly during phases of sharp growth. For this purpose, the actual trajectory of the integrated index of systemic financial risk was compared with the neural network model's predicted

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values. The integrated index of systemic financial risk is formed by aggregating normalized blockchain signals selected for their economic relevance.

First of all, the indicators were brought to a comparable scale using min-max normalization:

$$I_{norm} = \frac{X_t - X_{min}}{X_{max} - X_{min}}, \text{ where}$$

X_t – the actual value of the indicator at time t,

X_{min}, X_{max} – the minimum and maximum value of the indicator in the sample.

Next, after normalization, the integral index of systemic financial risk (Systemic Financial Risk Index, SFRI) was calculated as a weighted sum of normalized indicators:

$$SFRI_t = \sum_{i=1}^{n} w_i \cdot I_{i,t}, \text{ where}$$

w_i – weighting factors,

$I_{i,t}$ – normalized values of blockchain signals.

The weights are determined based on their relative importance in training the neural network model.

The predictive values of the integral index are obtained using an LSTM model trained on a historical time-series sample of blockchain signals, with a mechanism for accounting for previous time observations. The total sample was 24 observations, of which 70% were used to train the model and 30% to test its predictive ability.

The mean absolute error (MAE) and root mean square error (RMSE) were used to assess accuracy, allowing characterization of both the average magnitude of forecast errors and the model's sensitivity to peak risk values.

According to the test results, the RMSE is 0.018 and the MAE is 0.012, indicating a high level of agreement between the actual and predicted integral index values. The low level of error under conditions of sharp fluctuations (in particular, in the phase t15 - t16) confirms the model's ability to adequately reproduce the turning points in the dynamics of systemic financial risk.

A comparison of the actual and predicted trajectory of the integral index is shown in fig. 2.

Therefore, the analysis of the dynamics of the actual and forecast values of the index indicates the model's ability to correctly reproduce both the general risk trend and the turning points of sharp growth (in particular, in the period t15 - t16, when the peak value of 0.973 was recorded). The forecast deviation from the actual value during the phase of maximum risk growth does not exceed 0.029, indicating the model's high sensitivity to crisis signals.

The fig. 2 shows strong consistency in the directions of change between the actual and predicted indices, confirming the adequacy of the model's architecture and the correctness of the structuring of blockchain signals. The model's ability to reflect periods of accelerated risk escalation with minimal time lag is particularly indicative and is of fundamental importance for early response systems. During periods of market turbulence, the forecast curve not only reproduces the amplitude of fluctuations but also preserves their dynamic configuration, indicating that nonlinear dependencies and the cumulative effect of signals are taken into account.

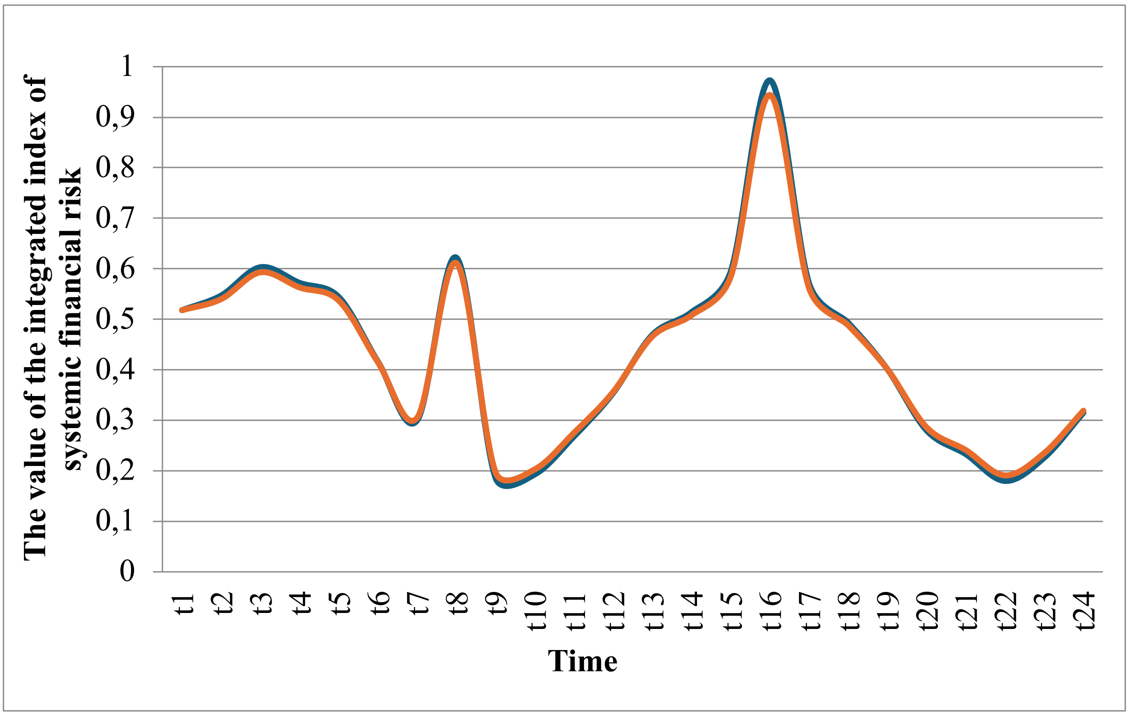

Fig. 2. Actual and predicted values of the integral index of systemic financial risk, normalized scale 0–1. Blue curve – actual index, red curve – network forecast.

Source: compiled by the author based on [11; 14]

The results show that integrating blockchain metrics into the neural network model increases sensitivity to structural changes in the market environment and reduces the information lag in detecting pre-crisis conditions. Therefore, the presented visualization serves not only an illustrative function but also provides empirical confirmation of the hypothesis regarding the prognostic potential of blockchain signals in the modeling of systemic financial risk.

The obtained results lay the methodological foundation for the further development of adaptive early warning models focused on digitized financial ecosystems, and open up prospects for expanding the toolset of macro-financial monitoring, taking into account the network nature of modern markets.

Conclusions. In the study, a holistic approach to predicting systemic financial risk was developed, combining the grouping of blockchain signals with neural network modeling. The classification of blockchain metrics by functional groups helped structure the information array of digital market data and provide them with an economically meaningful interpretation as potential indicators of instability. The developed neural network model accounts for temporal dynamics and complex nonlinear relationships among indicators, which are critical for risk analysis in a digitalized financial environment. The construction of an integrated index of systemic financial risk enabled aggregation of disparate signals into a coherent analytical model suitable for further monitoring.

Empirical validation confirmed the model's ability to adequately reproduce risk dynamics and to timely identify the phases of its escalation. The results show that integrating blockchain signals into the predictive architecture increases sensitivity to structural changes in the market environment and reduces the response time lag compared to traditional approaches.

So, the article substantiates the use of structured blockchain signals for modeling systemic financial risk and empirically confirms the effectiveness of neural network tools. The proposed approach opens new methodological possibilities for macro-financial analysis and lays the foundation for the development of adaptive early warning systems in digital financial ecosystems.

Prospects for further research include expanding the spectrum of digital indicators, integrating macroeconomic variables into multifactor models, and leveraging ensemble architectures and adaptive learning mechanisms. An important direction is also deepening the theoretical understanding of the obtained results from the standpoint of modern concepts of financial instability and the network nature of market interactions.

References

1. Лютюк Л., Гнатчук Є., Пончовна О. Інформаційні технології прогнозування фінансових ринків за допомогою нейронних мереж. *Вісник Хмельницького національного університету. Серія: Технічні науки.* 2024.

Т. 345. № 6 (2). С. 179–184. DOI: https://doi.org/10.31891/2307-5732-2024-345-6-27.

2. Семененко Т. О., Домрачев В. М. Прогнозування динаміки макроекономічних показників. *Вісник СумДУ. Серія «Економіка».* 2019. № 3. С. 110–116. DOI: https://doi.org/10.21272/1817-9215.2019.3-14.

3. Мазютинець Г. В., Шаркаді М. М. Модель багаторівневої нейромережі визначення рівня фінансової безпеки компанії. *Науковий вісник Ужгородського університету. Серія «Математика і інформатика».* 2022. Т. 40, № 1. С. 175–194. DOI: https://doi.org/10.24144/2616-7700.2022.40(1).175-194.

4. Кушнір М. Я., Токарєва К. А. Використання систем штучного інтелекту у задачах прогнозування фінансових індексів: огляд наукових джерел. *Радіоелектронні і комп'ютерні системи.* 2020. № 3. С. 108–117. URL: http://nbuv.gov.ua/UJRN/recs_2020_3_13 (access date: 30.07.2024).

5. Осика С. Г., Куликов К. Б. Платформа Aladdin як базовий інструмент функціонування BltckRock. *Економіка і суспільство.* 2024. № 64. DOI: https://doi.org/10.32782/2524-0072/2024-64-14.

6. Бебешко Б. Аналіз методів та моделей прогнозування ринку цифрових криптовалют. *Кібербезпека: освіта, наука, техніка.* 2022. № 2 (18). С. 163–174. DOI: https://doi.org/10.28925/2663-4023.2022.18.163174.

7. Клименко В. Застосування інструментів штучного інтелекту для підвищення точності прогнозування продажів у сфері цифрового підприємництва. *Економіка та суспільство.* 2024. № 68. DOI: https://doi.org/10.32782/2524-0072/2024-68-140.

8. Фаріон В., Гомотюк А., Назар Р., Турчин С. Використання штучного інтелекту для прогнозування фінансових показників. *Економічний аналіз.* 2024. Т. 34, № 2. С. 327–337. DOI: https://doi.org/10.35774/econa2024.02.327.

9. Приймук В. В. Впровадження штучного інтелекту у фінансову діяльність підприємства. *Збірник наукових праць Державного податкового університету.* 2023. № 1. С. 183–198. DOI: https://doi.org/10.33244/2617-5940.1.2023.183-198.

10. Basheri M., Ragab M. Robust financial market share prediction using Intuitionistic Possibility Fermatean Neutrosophic Soft Set. *International Journal of Neutrosophic Science.* 2024. Vol. 24, № 3. P.115–126. DOI: https://doi.org/10.54216/IJNS.240310.

11. AL-Ashmori A., Thangarasu G., Dominic P. D. D., Al-Mekhlafi A.-B. A. A readiness model and factors influencing blockchain adoption in Malaysia's software sector: a survey study. *Sustainability.* 2023. Vol. 15, №. 16. 12139. DOI: https://doi.org/10.3390/su151612139.

12. Li A. W., Bastos G. S. Stock market forecasting using deep learning and technical analysis: a systematic review. *IEEE Access.* 2020. Vol. 8. P. 185232–185242. DOI: https://doi.org/10.1109/ACCESS.2020.3030226.

13. Sako K., Mpinda B. N., Rodrigues P. C. Neural networks for financial time series forecasting. *Entropy.* 2022. Vol. 24, № 5. 657. DOI: https://doi.org/10.3390/e24050657.

14. Shahi T. B., Shrestha A., Neupane A., Guo W. Stock price forecasting with deep learning: a comparative study. *Mathematics.* 2020. Vol. 8, № 9. 1441. DOI: https://doi.org/10.3390/math8091441.

15. Sulandari W., Subanar S., Suhartono S., Utami H., Lee M. H., Rodrigues P. C. SSA-based hybrid forecasting models and applications. *Bulletin of Electrical Engineering and Informatics*. 2020. Vol. 9, № 5. P. 2178–2188. DOI: https://doi.org/10.11591/eei.v9i5.1950.

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