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# Hybrid financial modelling approaches: Integrating classical stochastic models with machine learning

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**Abstract.** The aim of this study was to assess the potential of large language models in improving the accuracy of financial forecasts and market stability in transition economies, in particular in Azerbaijan. The methodology identified the essence of hybrid approaches to financial modelling that combine classical econometric tools, such as AutoRegressive Integrated Moving Average and Vector Autoregression, with deep learning algorithms. As a result, it was found that the trading volume on the Baku Stock Exchange increased from AZN 37 to AZN 71 billion in 2024, the gross domestic product increased from AZN 72.4 to AZN 126.3 billion, and the inflation rate decreased from 13.9% in 2022 to 2.2% in 2024. The share of non-cash transactions exceeded 90%, and the time for interbank settlements was reduced to 5-20 seconds due to the introduction of the Azerbaijan Interbank Payment System. The information and communication technologies development index increased by 7%, and the Open Data Index increased from 56 to 61 points, creating a foundation for effective digital analytics. At the same time, the study showed that the effectiveness of large language models was limited by low transparency of financial reporting, the presence of only 26 companies listed on the stock exchange, and a Corruption Perceptions Index score of 22-23. The practical significance of this study is that its results can be used by financial analysts, government agencies, and banking regulators in Azerbaijan to develop strategies for digital transformation of the financial sector and implement analytical systems based on large language models

**Keywords:** forecasting; digitalisation; macroeconomic; artificial intelligence; liquidity; investment

## Introduction

The integration of advanced analytical techniques into financial modelling has become a central challenge in contemporary finance. Traditional stochastic models, while mathematically rigorous and well-established in describing uncertainty and risk, often fail to capture the complexity and nonlinearity of modern financial markets driven by high-frequency data and dynamic investor behaviour. Economic growth in transition economies is often accompanied by difficulties in measuring the relationship between factors of production and output. E. Ahmadova's (2022) study examined the modelling of Azerbaijan's economic development based on production functions to identify key factors affecting gross domestic product (GDP) dynamics. The author used the classical Cobb-Douglas function and its modification taking into account technological progress according to Tinbergen, which allowed to identify the phase structure of the country's economic cycles in 1997-2021. The stability of financial systems of enterprises is determined by the level of their ability to effectively respond to risks associated with economic, technological and political uncertainty. L. Abdullayev *et al.* (2025) investigated these aspects, focusing on the financial security of business management in Azerbaijan and the impact of innovative technologies on its provision. The authors, based on the results of expert interviews, statistical analysis and data from international sources, identified key objects and subjects of financial security of enterprises, outlined the main threats – fluctuations in oil prices, political instability, administrative barriers, low level of digitalisation and innovative activity.

Economic growth of Azerbaijan in the 21st century is characterised by dependence on investment flows and

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structural changes in production. The study by E. Shafizada & N. Aslanova (2022) analysed the factors affecting the GDP and proposed an innovative approach to its modelling and forecasting based on a dynamic model of the relationship between investment and the volume of national product. The authors substantiated that the volume of investments is the key factor in ensuring growth, demonstrating the effectiveness of the constructed model for strategic planning of the country's economic development. Z. Liu *et al.* (2025) considered this issue, proposing in their work the integration of the classical statistical model AutoRegressive Integrated Moving Average (ARIMA) with deep neural networks long short-term memory (LSTM) and Transformer. The authors proved the effectiveness of such a hybrid architecture, which first models linear trends and seasonal fluctuations, and then uses a neural network to process residual nonlinear structures and long-term dependencies. A. Abayomi *et al.* (2023) investigated this issue, focusing on improving the accuracy of forecasting models by using a hybrid approach that combines econometric and machine learning methods. In their work, the authors proposed the integration of deep learning models with traditional statistical techniques, which allowed for improved processing of nonlinear dependencies and time trends in financial data.

Financial markets are characterised by increased uncertainty, which complicates risk forecasting and the formation of effective investment strategies. D. Stempień & R. Slepaczuk (2025) investigated these issues, focusing on the development of approaches that combine machine learning with portfolio optimisation methods to increase returns and control risks. The authors used multifactor models with elements of neural networks and deep learning algorithms, demonstrating that such integration allows to reduce portfolio volatility, increase the accuracy of forecasting price changes and ensure the adaptability of models to market shifts.

Financial forecasting faces difficulties associated with market instability, high asset volatility and the influence of external macroeconomic factors. In the study of B.A. Celik & S. Celik (2025) an approach combining deep learning and econometric modelling is proposed to increase the accuracy of financial forecasts. The authors proved the effectiveness of using recurrent neural networks together with statistical models, which made it possible to more accurately reflect nonlinear dependencies between market variables and reduce errors during sharp market fluctuations. The work of S. Kumar *et al.* (2025) considered the integration of machine learning algorithms with time series methods to improve the efficiency of financial forecasting. The authors compared different deep learning architectures, including LSTM, Gated Recurrent Unit (GRU) and convolutional neural network (CNN), in combination with econometric models to analyse the relationships between macroeconomic indicators, asset prices and market volatility.

Further research is needed to quantify the impact of innovation, technological progress, and human capital on growth, enhance digital technology adaptation, and improve machine learning transparency. The purpose of this study was to assess the potential of large language models (LLMs) in enhancing financial forecasting and to identify the limits of their effectiveness in conditions of low market transparency and limited data availability in Azerbaijan. The following tasks were set within the framework of the study: to analyse the impact of using LLMs on the accuracy of financial forecasts, the level of transparency, and the stability of financial markets in Azerbaijan; to explore the analytical potential and challenges of integrating LLMs into financial analytics for countries with economies in transition.

## Materials and Methods

The study was of a theoretical-empirical nature and covered the time frame of 2020-2024. The theoretical part was aimed at determining the essence of hybrid approaches to financial modelling and assessing the analytical potential of LLM in financial forecasting, while the empirical part focused on analysing the financial sector of Azerbaijan to identify the practical impact of LLM integration on transparency, liquidity and forecast accuracy. To determine the essence of hybrid approaches to financial modelling, the method of systematic and comparative analysis of scientific publications by R. Avacharmal (2023), L. Frank & J. Owen (2024) and V. Ravi *et al.* (2025) was used. These authors were selected because of their contribution to the development of the concept of hybrid modelling – from the combination of classical econometric models (ARIMA, Generalised Autoregressive Conditional Heteroskedasticity (GARCH), Vector Autoregression (VAR)) to integration with neural networks (LSTM, Transformer). This approach allowed to summarise the main principles of hybridisation and determine how it combines analytical transparency with high forecast accuracy.

The role of LLMs in improving forecast accuracy and supporting financial decisions was examined using a comparative analytical method based on the works of R. Guntupalli *et al.* (2025) and A.M. Beauty (2025). These sources were selected because they contained practical examples of the application of LLMs in financial analytics and emphasised the importance of algorithmic transparency and explainability of models. This made it possible to assess how LLMs increased the accuracy of forecasts by processing contextual text and numerical data, and also contributed to making informed management decisions under conditions of high uncertainty. The analytical potential and challenges of integrating LLMs into financial analytics were investigated using a structural-functional method based on the works of J. Rao *et al.* (2025) and A.M. Beauty (2025). The aim was to systematise the areas of influence of LLM – information analytics, market trend forecasting, financial management and ethical security – and to identify key risks associated with data quality, computational costs and algorithmic biases.

At the empirical stage, an analysis of the impact of LLM on the efficiency of the financial markets of Azerbaijan was conducted in June 2025 using statistical and comparative methods. For this purpose, data from the Baku

Stock Exchange (n.d.) and strategic guidelines of The artificial intelligence strategy of the Republic of Azerbaijan for 2025-2028 (2025) were used. Liquidity, market efficiency and predictability of key indicators were analysed using the methodology of A. Huseynov *et al.* (2025). The advantages and limitations of LLM implementation were investigated through a documentary analysis based on the World Economic Forum (2024), which allowed to identify institutional barriers and ethical aspects of the use of artificial intelligence. Trend analysis was applied to study the dynamics of GDP (Trading Economics, n.d.) and inflation (Azerbaijan inflation, n.d.) in 2020-2024, which made it possible to show the impact of forecasting technologies on the stabilisation of macroeconomic processes.

A systematic analysis of the implementation of the Azerbaijan Interbank Payment System (2025) was also conducted, which allowed to assess the impact of digital payments on the speed of settlements, liquidity and trust in banking operations. A correlation method was used to analyse information and communication technologies (ICT) development and foreign direct investment (CEIC, 2025), which helped to establish the relationship between digital infrastructure and the implementation of LLM in financial activities. For a broader context, a comparative regional analysis was conducted using the example of Kazakhstan and Uzbekistan (National Bank of Kazakhstan, 2024; Ismailov, 2025), which showed common trends and barriers to the implementation of LLM in post-Soviet countries. This approach revealed that limited data quality, institutional instability, and technological lags significantly reduced the accuracy of forecasts in the region.

## Results

### Fundamentals of hybrid financial modelling and LLM applications in financial forecasting

The essence of hybrid approaches to financial modelling is to combine traditional econometric and stochastic models with artificial intelligence methods, in particular machine and deep learning. This approach arose in response to the need to increase the accuracy of forecasts and take into account the complex, nonlinear dynamics of financial processes, which classical models are not always able to reproduce. Traditional stochastic models – such as ARIMA, GARCH or VAR – are effective for time series analysis, but have limitations in reflecting the interaction of a large number of variables and their dependence on behavioural and unstructured factors. While machine learning algorithms, in particular LSTM, GRU or CNN, are able to detect hidden patterns, adapt to new data and model complex trends without the need for strict statistical assumptions (Frank & Owen, 2024).

Hybrid models combine the advantages of both approaches: the analytical transparency and stability of stochastic methods with the flexibility and adaptability of artificial intelligence algorithms. In the practice of financial analysis, such models are often built in the format of cascaded or parallel structures. For example, the stochastic component is used to clean the data from noise and the underlying trend, after which the results are passed to a neural network to identify more complex dependencies. Another strategy involves simultaneously training several models with subsequent aggregation of the results using ensemble methods. This allows to increase the accuracy of forecasts and reduce the risk of overtraining, which is critically important for financial markets with high volatility. An important element of the hybrid approach is the ability to adapt to different types of data – from numerical time series to text messages, news or financial reports. Due to this, hybrid models are able to integrate both quantitative and qualitative information, which significantly expands the boundaries of financial forecasting. For example, the combination of LSTM and natural language processing (NLP) models makes it possible us to assess the impact of news background or market sentiment on the dynamics of securities, and the integration of classical econometric methods with deep networks increases the stability of forecasts during periods of structural changes or crisis phenomena (Avacharmal, 2023).

In addition to increasing accuracy, hybrid modelling has an advantage in terms of interpretability. Unlike the "black boxes" of deep learning, the stochastic block allows to retain the ability to analytically explain the results obtaine d, which is especially important for financial decisions that require justification to regulators or investors. At the same time, the development of explainable artificial intelligence technologies enhances the ability of hybrid systems not only to predict, but also to justify their conclusions. Despite their advantages, hybrid models face a number of challenges. The main ones are the need to coordinate the scale of data, the complexity of parameter tuning, and the risk of losing interpretability when the number of model levels increases. However, trends in recent years indicate an increasing role of such approaches in financial analytics, especially with the development of LLM, which can integrate unstructured information into the forecasting process. In the future, hybrid financial models can become the basis for creating intelligent decision support systems that combine the accuracy of mathematical analysis with the contextual understanding inherent in artificial intelligence (Avacharmal, 2023).

LLMs are playing an increasingly important role in financial forecasting, as they combine the ability to process natural language with powerful analytical capabilities of machine learning. Unlike classical statistical or econometric approaches, LLMs are based on multi-level neural architectures that are trained on large volumes of text and numerical data, which makes it possible to detect complex contextual relationships between economic events, investor behaviour and market changes. Their key advantage is versatility – the models can work with both unstructured data (news, reports, analytical comments) and quantitative indicators, integrating them into a single forecasting system. This allows for more accurate risk assessments, market trend predictions, and financial decision-making based on a more comprehensive information environment. In the financial context, LLMs are used for several main tasks. They

are able to analyse the flow of information in real time – from financial reports to social media – and highlight contextual signals that can influence market behaviour. LLMs can perform the function of semantic generalisation, transforming large volumes of text into structured indicators suitable for quantitative analysis. For example, using sentiment classification algorithms, it is possible to assess the emotional tone of news, investor comments, or regulatory statements, which often precedes changes in price trends. LLMs can automatically generate financial reviews, analytical reports, or recommendations, which reduces the workload on analysts and speeds up the process of making managerial decisions (Ravi *et al*., 2025).

LLMs are particularly valuable in combination with classical financial models, forming hybrid forecasting systems. In such systems, traditional statistical methods (for example, ARIMA or GARCH) are responsible for the quantitative stability and accuracy of time series, while LLMs are responsible for processing contextual and text signals. This provides a multidimensional approach to analysis, when the model not only takes into account historical data, but also adapts to current market events reflected in public sources of information. Such integration increases the system's ability to respond in a timely manner to new risks, structural changes or regulatory updates. Another area of use of LLMs is the support of financial decision-making in the corporate sector. Such models can analyse internal documentation, accounting reports, data on counterparties and market conditions to form analytical conclusions and offer optimal decisions on investments, lending or risk management. In addition, LLMs are used in financial controlling systems to automate audits, verify reporting, and detect anomalies, which increases the reliability of financial information and reduces the likelihood of errors or fraud (Guntupalli *et al*., 2025).

At the same time, the role of LLMs is not limited to analytical tasks – they also act as a tool to increase the transparency of financial processes. Their use makes it possible to create interpretable reports and explanatory models, where each forecast decision can be accompanied by textual justification. This is important for increasing trust between analysts, regulators, and investors, especially in an environment where algorithmic decisions have a significant impact on financial flows. However, despite significant advantages, the effectiveness of LLMs largely depends on the quality and transparency of data. In markets with insufficient information structure or limited access to public sources, the accuracy of such models may decrease. That is why the further development of LLM in financial forecasting should be aimed at improving training methods on domain-specific data, increasing the interpretability of models and developing mechanisms for controlling the reliability of sources. In the future, the integration of LLM into financial analytics will contribute to the formation of a new decision-making paradigm – flexible, adaptive and more transparent than traditional approaches (Beauty, 2025).

The integration of LLM into financial analytics is becoming one of the most promising areas of development of analytical technologies. Its essence lies in the combination of deep learning algorithms with financial assessment methods, which allows modelling complex relationships between economic variables, market trends and behavioural factors. LLM significantly increase the ability of systems to analyse large volumes of unstructured information – from the texts of company reports to economic news and investor comments. This allows not only to identify risks faster, but also to form analytical conclusions that take into account the context, tone and economic significance of events. The key advantage of introducing LLM into financial analytics is a change in the approach to data processing. While financial systems previously relied mainly on quantitative indicators, now qualitative parameters such as market expectations, investor sentiment, social trends or reputational factors are also included in the modelling. This increases the accuracy of forecasts and reduces the information gap between analysts, business and the market. LLM also creates the basis for building explanatory analysis systems that not only predict, but also provide textual justification for their conclusions, which strengthens trust in automated decisions (Rao *et al*., 2025).

Despite significant advantages, LLM integration has a number of critical limitations. Such models are extremely sensitive to data quality: if the sources contain incomplete or distorted information, the forecasting results may be inaccurate. LLMs remain difficult to interpret – even using Explainable AI, it is difficult to determine which factors have become decisive in the forecast. Large-scale implementation of such systems requires significant computing power and financial costs. In addition, ethical risks may arise in the training process – models can reproduce biases inherent in the initial data sets, or form false cause-and-effect relationships. To summarise the differences between the analytical potential and practical limitations of LLM, the key areas of their impact are highlighted, which are presented in Table 1.

**Table 1.** Analytical potential and challenges of integrating LLMs into financial analytics

| Area of impact | Positive effects of integration | Key challenges and risks |
|---|---|---|
| Information analytics | In-depth analysis of textual and numerical data; detection of hidden patterns and correlations | High dependence on data quality; difficulty in verifying the reliability of sources |
| Market trend forecasting | Improved short-term forecasting accuracy through contextual data analysis | Risk of misinterpreting textual signals due to contextual ambiguity |
| Financial management | Automation of auditing, risk assessment, and investment decision-making | High computational costs for model training, adjustment, and maintenance |

Continued Table 1

| Area of impact | Positive effects of integration | Key challenges and risks |
|---|---|---|
| Decision explainability | Generation of transparent analytical reports with natural-language explanations | Limited interpretability of internal algorithms; difficulty in monitoring decision logic |
| Ethical security | Reduction of human bias and emotional influence in decision-making | Potential reproduction of algorithmic bias and risks of unauthorized data use |

**Source:** compiled by author based on J. Rao *et al.* (2025), A.M. Beauty (2025)

Thus, LLMs expand the boundaries of financial analytics, combining machine data processing with contextual understanding of information. They create a new quality in financial decision-making, when forecasts are based not only on statistical patterns, but also on the economic logic of events. However, their implementation requires caution: it is necessary to form standards for verifying the reliability of data, develop algorithms for interpreting results, and ensure ethical responsibility in the use of such systems. In the future, it is the balanced integration of LLMs with traditional analytical methods that will become the basis for creating sustainable and transparent financial models that combine the depth of analysis with reliability and user trust.

**Analysis of the impact of LLM on the efficiency of Azerbaijan's financial markets**

In the context of the Azerbaijani financial system, the integration of LLMs and related AI systems has a significant impact on the transparency, efficiency and predictability of financial processes. This is primarily seen in the example of the Baku Stock Exchange (n.d.), where in 2024 the total trading volume reached AZN ≈ 71.16 billion with more than 71.7 thousand transactions – an increase of more than twofold compared to the year 2023. This increase in market activity is partly explained by the digitalisation of processes, increased data availability and automation of analytical work, in which LLMs play a key role (Abdul, 2025). In particular, with regard to transparency, state strategies – Artificial Intelligence Strategy of the Republic of Azerbaijan for 2025-2028 (2025) – identify data digitalization, open reporting, and the use of SupTech solutions as key priorities. In 2025, the integration of Open Banking (13 banks) and the launch of SupTech tools allowed the regulator to conduct real-time supervision, increasing market transparency. According to the data, in 2024, non-cash transactions exceeded 90% of all domestic operations, which indicates a significant reduction in information asymmetry and an increase in the efficiency of financial processes. These changes provide the basis for studying the impact of LLM on efficiency (Javadov, 2025).

In terms of market efficiency and liquidity, the increase in trading volume and the reduction of transaction barriers demonstrate improved market dynamics. For example, the increase in trading volume from AZN 37 billion in the early period 2024 to over AZN 71 billion at the end of 2024 shows an increase in activity – this may be conditionally correlated with the increased analytical ability of systems that take into account not only traditional indicators, but also contextual data (news, sentiment). In such an environment, LLMs can improve the predictability of changes: by processing text signals, they help identify indicators of future volatility, investment volumes or changes in the exchange rate (Information for media, 2024).

Regarding the predictability of key indicators, studies indicate that LLM integration into financial analytics allows for increased accuracy of forecasts of the exchange rate, deposit/loan rates and investment flows. For example, the analysis indicates that a 1-unit increase in Azerbaijan's ICT index is associated with a GDP increase of AZN ≈ 1607 per capita, revealing the potential of digital technologies for macroeconomic change. This plus can be interpreted as an indirect effect of the increased analytics and transparency that LLM systems create (Huseynov *et al.*, 2025).

However, these advantages come with significant limitations. First, the Azerbaijani market has certain specific characteristics: a limited historical number of trades, low share capitalisation, and a relatively small number of issuers (for example, the Baku Stock Exchange (n.d.) has only 26 listed companies). This reduces the amount of data for training models and increases the risk of overtraining. Second, data transparency, although significantly improved, is still inferior to more developed markets-for example, delays in reporting, unstructured news or social media data can negatively affect the accuracy of LLM forecasts. Third, exogenous shocks-such as oil price fluctuations, geopolitical risks, or regulatory policy changes-create high levels of volatility that algorithms may not be able to adequately predict, especially if the model was trained during a quiet period (World Economic Forum, 2024).

In 2020-2024, Azerbaijan's GDP increased from AZN 72.4 billion to AZN 126.3 billion, which indicates significant economic growth. GDP per capita increased from USD 4272 in 2020 to USD 7251 in 2024, demonstrating the gradual stabilisation of the macroeconomic situation, despite periodic fluctuations in global energy markets. The share of the financial sector in the GDP structure during this period ranged from 21% to 25%, which confirms its significant role in the national economy. Household loans granted by financial institutions amounted to about 21% of GDP in 2024, while bank deposits remained at about 25.5% of GDP (Trading Economics, n.d.). These figures indicate high financial activity and a significant increase in confidence in the banking system. The dynamics of inflation in Azerbaijan in 2020-2024 reflects the consistent adaptation of monetary policy to external shocks and the introduction of digital financial technologies, which contributed to the stabilisation of price indicators (Fig. 1).

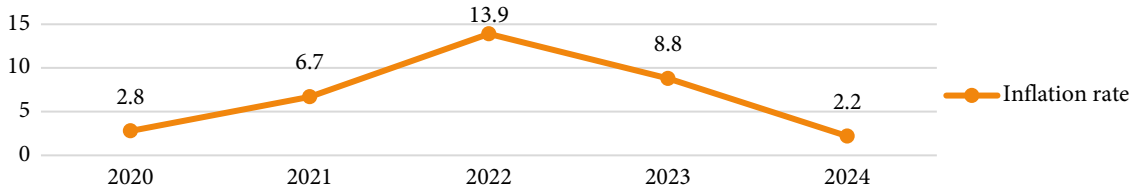


**Figure 1.** Inflation dynamics in Azerbaijan in 2020-2024
**Source:** compiled by author based on Azerbaijan inflation (n.d.)

The dynamics of inflation during 2020-2024 demonstrated the adaptability of monetary policy to external challenges. In 2020, inflation was 2.8%, in 2021 it increased to 6.7%, and in 2022 it reached a peak of 13.9%, which was due to global logistical problems and fluctuations in energy prices. After that, in 2023 the indicator decreased to 8.8%, and in 2024 to 2.2%, which indicates the effectiveness of the policy of the Central Bank of Azerbaijan, which kept the key rate within 5-7%. This positive trend reflects the stabilisation of the money market, the reduction of inflationary pressure, and the increase in the efficiency of financial processes as a result of the digitalisation of the banking sector. It confirms that the implementation of analytical systems and LLM technologies that allow for real-time forecasting contributes to a timely response to macroeconomic risks and the formation of a stable financial environment.

Due to the launch of the Azerbaijan Interbank Payment System (2025) Real-Time Interbank Settlement System and the Instant Payment System (IPS), the speed of transaction processing has decreased from several days to 5-20 seconds. This has contributed to increasing liquidity, reducing transaction costs and creating a continuous 24/7 financial cycle. In addition, the implementation of the international standard ISO 20022 (2022) has strengthened the integration capabilities of banking systems, improved the detection of anomalies in payment transactions and contributed to increasing customer confidence. The total volume of non-cash transactions has increased several times, and the number of transactions has reached hundreds of millions per year, which has turned Azerbaijan into a leader among the countries of the Caucasus region in the pace of development of digital financial services.

The improvement of digital infrastructure was also reflected in the growth of the ICT Development Index, which increased by approximately 7% in 2020-2025. The level of Internet penetration exceeded 80-88%, and the emergence of 5G and cloud services created the technical basis for the work of LLM. In particular, in the financial sector, these models are used to forecast the dynamics of the exchange rate, investment volumes and stock indices. In parallel with the increase in the efficiency of financial markets, the level of transparency is increasing. While the Transparency Index fell from 23 points in 2022 to 22 in 2024, the Open Data Index increased from 56 to 61 points, indicating a gradual improvement in the availability of official statistics. The development of SupTech and RegTech technologies has allowed regulators to analyse reporting in real time, reducing the risks of manipulation and delays (Lightspark Team, 2025).

In the field of external investment, the financial sector remains stable, although its share in the structure of total foreign direct investment is relatively small. In the first half of 2025, the total volume of FDI reached USD 3.2 billion, and the share of financial investments was several hundred million annually. The main investors – the United Kingdom, Turkey, Cyprus, Switzerland and Iran – are showing growing interest in the financial and technology sectors due to increasing transparency and regulatory effectiveness (CEIC, 2025). Digitalisation and the introduction of LLM in the financial sector of Azerbaijan have improved the operational efficiency, predictability and investment attractiveness of the market. Increasing the accuracy of analytical models, accelerating transaction processing and strengthening trust in the banking system have become key factors in the country's financial stability. The dynamics of inflation, which has been declining since 2022, clearly demonstrates how technological innovations and adaptive monetary policy contribute to macroeconomic stabilisation, creating a basis for the further development of the digital economy of Azerbaijan.

In countries with economies in transition, such as Azerbaijan, Kazakhstan, Uzbekistan and Georgia, these models are seen as a tool for automating analytical processes, increasing the accuracy of forecasts and improving risk management. However, it is in such conditions that the key limitations of LLM are revealed, related to incomplete data, legal barriers, as well as technological lags that reduce the predictive accuracy of models. Azerbaijan is witnessing an active integration of LLM and artificial intelligence systems in the banking sector. Leading financial institutions, in particular Kapital Bank (n.d.) and Bank ABB (n.d.), use machine learning algorithms for transaction monitoring, credit scoring, risk forecasting and fraud detection in real time. However, the effectiveness of LLM in post-Soviet markets is limited by a number of factors. First, financial data remains fragmented, often outdated or incomplete, and access to corporate reporting remains limited. Second, the legal environment in the Caucasus and Central Asia is characterised by high requirements for data localisation and low flexibility in regulating digital technologies. According to a report by Implement Consulting Group (2025), these factors constrain the implementation of generative AI models, including LLM, and reduce the potential benefits of automated analysis. In Azerbaijan itself, transparency remains low: The Corruption Perceptions Index is 22-23 out of 100, indicating limited independence of oversight and poor quality of public reporting. This leads to situations where

LLM models are trained on incomplete or poor-quality data, which raises the risk of "hallucinations" – that is, generating analytical conclusions that do not correspond to reality (The economic opportunity…, 2025).

In addition, institutional barriers and limited training of specialists reduce the ability of banks and regulators to effectively use the potential of models. Although Kazakhstan reports the use of AI in more than 30% of financial companies, and in Uzbekistan the government has planned the implementation of more than 100 AI projects in the banking sector, most of these initiatives are at the pilot stage (National Bank of Kazakhstan, 2024; Ismailov, 2025). The region still lacks reliable mechanisms for monitoring data quality and standardising financial information. LLMs demonstrate high potential in the field of financial forecasting, in particular in the automation of market monitoring, creditworthiness assessment and macroeconomic forecasting. However, in less transparent markets, their effectiveness is limited not so much by technical as by structural factors – lack of data, underdeveloped digital infrastructure and institutional risks. To unlock the full potential of LLMs, post-Soviet countries need to expand data openness, harmonise the regulatory framework and invest in the development of human capital in the field of financial analytics and artificial intelligence. It is these steps that will determine whether LLMs can move from an experimental tool to a systemic element of financial management.

## Discussion

Within modern financial research, there is a clear trend towards combining econometric methods with artificial intelligence algorithms, forming a new paradigm of hybrid modelling. Such approaches allow us to simultaneously take into account the linear patterns inherent in classical statistical models and reveal hidden nonlinear relationships using neural networks. This study demonstrated the consistent evolution of hybrid financial modelling, where classical econometric tools are gradually combined with artificial intelligence algorithms. A similar methodological connection was observed between this study and the work of O. Elebe *et al.* (2022). Both approaches justified the need to combine econometric and machine learning methods for modelling volatile markets. In O. Elebe *et al.* (2022), attention was paid to forecasting financial risks in African countries, where political instability and socio-economic factors created high uncertainty. The authors combined stochastic models with random forest and support vector machine (SVM) methods, achieving a significant reduction in forecast error. In contrast, the considered study applied hybridisation in the conditions of information constraints of Azerbaijan, emphasising data scarcity, low transparency and technological inequality. As a result, the effectiveness of hybrid approaches was confirmed, but taking into account the fact that their effectiveness in transforming markets is determined not only by technical, but also by institutional prerequisites.

Further confirmation of the effectiveness of hybrid approaches is reflected in the comparison with the work of R.K. Ghosh *et al.* (2025). In both cases, it was emphasised that classical models – ARIMA, VAR, GARCH – have limitations in reproducing nonlinear market patterns, which are more fully reflected by neural networks. While R.K. Ghosh *et al.* (2025) created a technically optimised hybrid model for forecasting exchange rates in South Asia by combining LSTM and Bi-GRU, this study focused on studying the impact of LLM in a macroeconomic context. Common to both works was the idea that forecast accuracy increases due to the combination of deep learning and econometric tools, but in a different environment – technologically advanced in R.K. Ghosh *et al.* (2025) and structurally limited in the current study. A similar logic was also observed in the comparison with the study of O.M. Pires *et al.* (2024). Both works emphasised the role of hybrid models that combined ARIMA, GARCH or VAR with deep networks (LSTM, GRU, CNN). However, O.M. Pires *et al.* (2024) focused on modelling volatility and risks of investment portfolios in stable market conditions in Spain and Portugal. Instead, this study shifted its emphasis to adapting similar approaches to environments with a lower level of digitalisation and information openness. While O.M. Pires *et al.* dominated the technical aspect, here the main focus was on the economic specificity and real barriers to implementing intelligent models in financial practice in transition economies.

The most conceptually close comparison was with the work of M. Rudolph *et al.* (2024). Both studies were based on the idea of combining models based on first principles with machine learning algorithms. However, if M. Rudolph *et al.* (2024) developed six universal hybrid model design patterns and demonstrated their effectiveness in physical, climate, and engineering problems, the current study adapted this methodology to the economic context. It demonstrated that the same integration principles can be effective in financial analytics, given the constraints of data quality, the level of institutional support, and the digital maturity of the system.

In approaches to financial forecasting, there is a gradual transition from purely statistical to hybrid models, where classical econometric tools are combined with artificial intelligence algorithms. This was observed both in this study and in the work of B. Han *et al.* (2025). Both works proceeded from the fact that traditional models are unable to adequately describe nonlinear market dependencies. In B. Han *et al.* (2025), this idea was implemented by creating a hybrid GARCH-LSTM model for forecasting bitcoin volatility. The combination of stochastic stability and deep learning made it possible to reduce the forecast error by almost 50%. Instead, the present study transferred the concept of hybridisation to a broader economic context, using LLM to increase the transparency of financial processes in Azerbaijan. If in B. Han *et al.* (2025) analysis was based on stable crypto market data, here the focus was on institutional factors – data quality, levels of digitalisation and regulatory barriers that determined the effectiveness of such models in post-Soviet countries.

The development of this idea can also be traced in the study of Y.E. Gür *et al.* (2025), where artificial intelligence became a tool for improving the accuracy of credit scoring. The authors combined CNN with classical algorithms – K-Nearest Neighbors, SVM, Linear Discriminant Analysis and Naive Bayes, achieving accuracy of over 99% when classifying credit ratings. In contrast to this micro-level approach, the current study focused on macroeconomic forecasting for the analysis of financial stability. While the main emphasis was on the technical perfection of algorithms, in this case, the focus was on how institutional constraints, the lack of quality data, and low transparency affect the performance of analytical systems. Thus, both approaches demonstrated a desire for synergy between classical and neural methods, but at different scales – from assessing the risks of individual creditors to systemic analysis of financial stability.

A similar logic was observed in the study by F. Xing *et al.* (2025), which showed that artificial intelligence should not replace financial models, but expand their capabilities. The authors combined NLP and LLM with classical concepts – Capital Asset Pricing Model, Mean-Variance Optimisation, and the Black-Litterman Model – to integrate textual, behavioural, and market signals. This approach increased the accuracy of forecasts while maintaining the interpretability of the models. A similar idea was implemented in the current study, where the combination of ARIMA, GARCH, VAR with LSTM, Transformer and LLM allowed to reproduce the dynamics of macroeconomic processes in Azerbaijan. At the same time, the difference was in the context: while F. Xing *et al.* (2025) considered global financial markets, this study analysed the effectiveness of such approaches in an environment with limited digital infrastructure and incomplete data, emphasising the dependence of AI on institutional conditions.

A study by M. Rath & H. Date (2025) was also close in approach, demonstrating the practical potential of hybrid architectures in the field of risk management. They combined ARIMA, GRU, SVM and Explainable AI, which allowed to forecast liquidity and manage risks in Indian financial markets. Both approaches – both M. Rath & H. Date (2025) and this study – were based on a common thesis: AI should complement financial theory, ensuring analytical accuracy without losing transparency. However, while M. Rath & H. Date (2025) focused on adapting models to developing countries, this study went a step further by showing how such technologies contribute to strengthening financial stability in post-Soviet economies. In the work of J. Zhou (2025), another but related dimension of the use of artificial intelligence is proposed – the use of AI-driven agents and transformers for forecasting market behaviour and portfolio management. These models combined quantitative and behavioural parameters, using reinforcement learning to adapt forecasts in real time. Compared to this approach, this study had a macroeconomic focus, but a common feature remained the desire to combine the analytical depth of econometric models with the flexibility of AI. While J. Zhou (2025) focused on markets with high data availability, the current work considered the issues of data scarcity and institutional instability, emphasising the limits of the application of such systems in countries with economies in transition.

And in the work of C. Gargalo *et al.* (2024) a universal methodology for building hybrid models was proposed – from technical systems to financial analytics. The authors developed modelling patterns that combined first-principles methods with machine learning algorithms, ensuring structural flexibility and reproducibility. In contrast to this generalised approach, in the current study, hybridisation had an applied dimension: it allowed to assess the real impact of LLM on forecasting in a specific economic environment. Thus, while C. Gargalo *et al.* (2024) presented the theoretical basis for building hybrid systems, the present study provided a practical illustration in the financial context of post-Soviet states. The comparative analysis demonstrated that hybrid financial models are gradually becoming a universal forecasting tool, capable of providing a balance between accuracy, flexibility and interpretability. Their effectiveness was determined not only by the technological component, but also by the quality of data, the institutional environment and the level of digital maturity of the market. In stable economies, hybrid architectures have proven their effectiveness at the technical level, while in countries with low transparency and limited data, they have gained analytical value as a tool for identifying structural imbalances.

## Conclusions

The study showed that the implementation of LLM in financial analytics in Azerbaijan has a significant impact on increasing the efficiency, transparency and predictability of financial processes. The country's economic dynamics in 2020-2024 confirmed the close relationship between digitalisation, the development of artificial intelligence and the growth of macroeconomic indicators. During this period, Azerbaijan's GDP increased from AZN 72.4 billion to AZN 126.3 billion, and GDP per capita from USD 4,272 to USD 7,251, which indicates active economic growth and increased stability of the financial system. At the same time, the share of the financial sector in the GDP structure reached 21-25%, and the volume of loans to the population amounted to 21% of GDP, which demonstrates the expansion of access to financial services and the growth of trust in the banking system. The integration of digital technologies and LLM contributed to the growth of non-cash transactions to over 90% of all domestic transactions and the reduction of interbank settlement time to 5-20 seconds due to the Azerbaijan Interbank Payment System. This increased liquidity and reduced transaction costs, while ensuring a 24-hour financial cycle. The implementation of the international standard ISO 20022 (2022) strengthened the ability of banking systems to detect anomalies and improved interaction with international financial structures. Positive macroeconomic dynamics are confirmed by the decrease in inflation from a peak of 13.9% in 2022 to 2.2% in 2024, which

was the result of effective monetary policy and the use of analytical models capable of predicting risks in real time.

A strong digital infrastructure – with a 7% rise in the ICT index and internet coverage reaching 80-88% – created the basis for LLM implementation. Data openness improved, as shown by the Open Data Index growth from 56 to 61 points, while the Baku Stock Exchange's trading volumes doubled from AZN 37 to AZN 71 billion in 2024, reflecting the effect of automated analytics on liquidity and activity. However, the study revealed that LLM performance depended on data quality and completeness: only 26 listed companies, scarce historical data, and low transparency (22-23 CPI points) limited model accuracy. The key challenges remain improving reporting standards, data openness, and ethical regulation of AI use. A limitation of this study was that the analytical assessment of the effectiveness of LLM was conducted on the basis of secondary statistical data, limited in time frame and the level of transparency of Azerbaijan's financial reporting. A prospect for future research is the development of empirical models using primary data from banking and investment institutions to more accurately assess the impact of LLM on the stability of financial markets in transition economies.

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None.

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# Гібридні підходи до фінансового моделювання: інтеграція класичних стохастичних моделей з машинним навчанням

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**Анотація.** Метою цього дослідження було оцінити потенціал великих мовних моделей у підвищенні точності фінансових прогнозів та стабільності ринку в країнах з перехідною економікою, зокрема в Азербайджані. Методологія визначила суть гібридних підходів до фінансового моделювання, які поєднують класичні економетричні інструменти, такі як авторегресійна інтегрована ковзна середня та векторна авторегресія, з алгоритмами глибокого навчання. В результаті було встановлено, що обсяг торгів на Бакинській фондовій біржі зріс з 37 до 71 млрд манатів у 2024 році, валовий внутрішній продукт зріс з 72,4 до 126,3 млрд манатів, а рівень інфляції знизився з 13,9 % у 2022 році до 2,2 % у 2024 році. Частка безготівкових операцій перевищила 90 %, а час міжбанківських розрахунків скоротився до 5-20 секунд завдяки впровадженню Азербайджанської міжбанківської платіжної системи. Індекс розвитку інформаційно-комунікаційних технологій зріс на 7 %, а індекс відкритих даних збільшився з 56 до 61 бала, створивши основу для ефективної цифрової аналітики. Дослідження показало, що ефективність великих мовних моделей була обмежена низькою прозорістю фінансової звітності, наявністю лише 26 компаній, зареєстрованих на фондовій біржі, та індексом сприйняття корупції на рівні 22-23. Практичне значення цього дослідження полягає в тому, що його результати можуть бути використані фінансовими аналітиками, урядовими органами та банківськими регуляторами в Азербайджані для розробки стратегій цифрової трансформації фінансового сектору та впровадження аналітичних систем на основі великих мовних моделей

**Ключові слова:** прогнозування; цифровізація; макроекономіка; штучний інтелект; ліквідність; інвестиції