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ARTIFICIAL INTELLIGENCE IN ECONOMIC ANALYSIS AND FORECASTING OF THE REPUBLIC OF MOLDOVA

Abstract. The relevance of this study is driven by the growing need for high-precision macroeconomic forecasting tools for the Republic of Moldova — a small open economy that is historically highly exposed to external price shocks, significant energy import dependence, and continuous real sector volatility. Traditional forecasting methods have shown their limitations during recent crisis periods, emphasizing the demand for more advanced analytical frameworks. The purpose of this research is to conduct a comprehensive comparative assessment of the predictive capacity of three distinct model classes — multiple linear regression (MLR), Autoregressive Integrated Moving Average (ARIMA), and Long Short-Term Memory (LSTM) recurrent neural networks. These models are applied to forecasting Moldova's inflation rates and Gross Domestic Product (GDP) growth based on macroeconomic data spanning the period from 2018 to 2025. The empirical information base is derived exclusively from official publications provided by the National Bank of Moldova (NBM) and the National Bureau of Statistics of the Republic of Moldova. To ensure methodological rigor, the quality and accuracy of the models were evaluated and cross-validated using standard statistical metrics, specifically Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The comparative results compellingly show that the deep learning LSTM model demonstrates significant and consistent superiority over traditional econometrics. Specifically, it reduces the RMSE of inflation forecasts from 1.139 (linear regression) and 0.973 (ARIMA) down to 0.354, while improving the MAPE from 21.4% and 17.3% to a highly accurate 6.85%, respectively. Furthermore, a generated scenario forecast for the upcoming 2026–2027 period indicates that inflation will likely consolidate near 5.0% and 4.5%, which remains entirely consistent with the NBM's established target corridor. Additionally, GDP growth in the baseline scenario is projected at stable rates of 2.2% in 2026 and 3.0% in 2027. The practical value and novelty of this study lie in the potential direct integration of the proposed AI-driven predictive models into the strategic analytical systems of the National Bank and the Ministry of Economic Development and Digitalization of the Republic of Moldova, thereby enhancing policy formulation under uncertainty.

Keywords: *Artificial Intelligence, Macroeconomic Forecasting, LSTM, ARIMA, Moldova*.

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Introduction. Digital transformation in national economies is establishing new standards for the analytical instruments of public administration. The period from 2022 to 2025 clearly exposed the limitations of traditional forecasting systems: none of the basic econometric models was able to adequately predict the inflationary shock of 2022, when consumer prices increased by 28.7% year-on-year. This has confronted both the academic community and regulatory authorities with the need to transition to more adaptive forecasting methods. In this context, artificial intelligence methods – most notably recurrent neural networks of the LSTM class – represent a promising, though still insufficiently studied, analytical tool in relation to the Moldovan market.

Based on the identified gaps in analytical practices, the aim of this research is to conduct a comparative assessment of the predictive capacity of traditional econometric models versus deep learning neural networks applied to macroeconomic forecasting in Moldova. To achieve this aim, the following tasks were formulated: (1) to systematize the theoretical foundations of applying AI in economic forecasting; (2) to develop and train MLR, ARIMA, and LSTM models using Moldovan statistical data (2018–2025); (3) to evaluate and compare the models' performance using RMSE, MAE, and MAPE metrics; and (4) to generate baseline scenario forecasts for inflation and GDP growth for 2026–2027. The object of the research is the macroeconomic dynamics of the Republic of Moldova, specifically the trajectory of inflation and GDP growth. The subject of the research encompasses the mathematical and instrumental models (MLR, ARIMA, LSTM) utilized for macroeconomic forecasting under conditions of high economic volatility.

Literature Review. Contemporary macroeconomic literature demonstrates a persistent shift from traditional econometric methods to machine learning tools in forecasting under conditions of high volatility (Liu et al., 2024). The classical paradigm, which relies on assumptions of time-series stationarity and normally distributed residuals, has demonstrated its vulnerability during periods of global shocks such as the COVID-19 pandemic and the subsequent global energy crisis. In particular, for Small Open Economies (SOEs), including the Republic of Moldova, external shocks are transmitted into domestic inflation and output contraction with minimal time lag, rendering linear autoregressive models, including ARIMA and VAR, insufficiently flexible (Jönsson, 2025).

As Gheorghiu and Popescu (2024) note, central banks around the world are actively integrating deep learning algorithms into monetary policy calibration processes. This is because Long Short-Term Memory (LSTM) architectures are capable of identifying hidden nonlinear patterns and capturing long-term dependencies among macroeconomic variables without requiring a rigid specification of the functional form of the equations (Purtov, 2024; Kadang, 2026). Moreover, the findings of Lenzu (2026) emphasize that artificial intelligence not only improves the accuracy of point forecasts, but also enables regulators to conduct more robust scenario analysis when formulating responses to inflationary challenges.

In the context of Emerging Markets, the application of machine learning yields even more tangible results. Using a sample of developing countries, Khan and Ahmed (2024) demonstrated that ensemble methods and deep neural networks outperform traditional approaches in inflation forecasting, especially when high-frequency data, such as foreign exchange reserves and exchange rates, are used as predictors. Similar conclusions were reached by Tiwari (2024) in the analysis of large macroeconomic datasets, where machine learning methods reduced the root mean square error (RMSE) by 15–20% compared with structural macroeconomic models.

Particular attention in the literature has been devoted to the nuances of forecasting over extended horizons. As Gonçalves (2023) notes, when the forecasting horizon exceeds four quarters, the accuracy of deep learning architectures may decline due to the error accumulation effect, which makes the use of hybrid approaches advisable (Oprea, 2025).

For the Republic of Moldova, the problem is exacerbated by the lack of long historical time series free from structural breaks. The transition to a market economy, the crises of 1998, 2008, and 2014, and the unprecedented inflationary surge of 2022, which peaked at 34.6% year-on-year, render pre-2010 historical data only weakly informative for training modern models (Rusu & Munteanu, 2025). Under these conditions, the application of methods that are robust to outliers and capable of “forgetting” obsolete information an ability embedded in the gate architecture of LSTM appears to be the most promising direction (Ursu, 2024).

Despite the growing interest in this topic, no systematic studies have yet been conducted that are devoted exclusively to a comparative analysis of econometric and neural network models based solely on data from the Republic of Moldova. Most existing studies either consider Moldova within panel datasets of Eastern European countries (Câmpeanu & Ionescu, 2025) or focus on individual indicators, such as the unemployment rate. The present study seeks to fill this gap by proposing a methodologically rigorous approach to the application of artificial intelligence in the macroeconomic analysis of a specific small open economy.

Research Methodology

1. Theoretical Foundations of AI in Economic Forecasting

Multiple linear regression (MLR) remains a fundamental method of quantitative economic analysis and is expressed by the following equation:

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Table 1. Comparative Analysis of Forecasting Methods

Characteristic	MLR	ARIMA	LSTM
Type of dependencies	Linear	Linear	Nonlinear
Robustness to shocks	Low	Medium	High
Computational Complexity	Low	Medium	High

Table 2. Comparison of the Forecasting Accuracy of the Models

Model	RMSE	MAE	MAPE (%)
MLR	1,139	0,907	21,4
ARIMA (2,1,1)	0,973	0,769	17,3
LSTM	0,354	0,283	6,85

$$y_t = \beta^0 + \beta^1 x_{1t} + \beta^2 x_{2t} + \ldots + \beta nx_{nt}) + \varepsilon_t. \quad (1)$$

ARIMA (Autoregressive Integrated Moving Average) – a classical time-series model:

$$\Phi \frac{d}{\rho}_{(B)}(1-B)y_t = \Theta_{q(B)\varepsilon t}. \quad (2)$$

LSTM (Long Short-Term Memory) – an architecture of a recurrent neural network specifically designed to process sequential data and overcome the vanishing gradient problem. Formally, the model is described by the following system of equations:

$$\begin{gathered} f_t = \sigma(W_f [h_{\{t-1\}}, x_t] + b_f), \\ C_t = f_t * C_{\{t-1\}} + i_t * C\sim t, \\ h_t = o_t * tanh(C_t). \end{gathered} \quad (3)$$

2. Data Sources of the Republic of Moldova

The empirical foundation of the study was constructed using two key official sources: the National Bank of Moldova (NBM) [1] and the National Bureau of Statistics (NBS) [2]. The analysis of the time series revealed structural breaks, most notably in 2020 due to the pandemic and in 2022 due to the energy crisis, which necessitates the use of robust adaptive algorithms.

3. Research Methodology

To ensure an objective comparison of the models, three standard evaluation metrics were employed: RMSE, MAE, and MAPE. Data normalization was performed using the Min-Max method:

$$x' = \frac{(x - x_{min})}{(x_{max} - x_{min})}. \quad (4)$$

Pseudocode of the LSTM Training Algorithm:

For each step t in [k,n]:

$$\begin{aligned} & X_{batch} = X_{norm[t-k:\,t]}, \\ & yhat_t = LSTM(X_{batch};\ W), \\ & L = MSE(y_t, y_{hat_t}), \\ & W <- W - lr * \frac{dL}{dW}. \end{aligned} \quad (5)$$

4. Forecasting Results

A retrospective analysis of the data indicates that Moldova's inflation series for the period 2018–2025 contains a pronounced structural break in 2022. Neither the MLR model nor ARIMA was able to adequately reproduce this discontinuity. The LSTM model partially captured the build-up of inflationary pressure and produced an error that was two to three times lower than that of the competing approaches.

5. Discussion of Results

The study confirmed the hypothesis that the use of LSTM for forecasting inflation and GDP in the Republic of Moldova provides higher predictive accuracy, with RMSE reduced to 0.354, compared with MLR and ARIMA. AI-based models may therefore be recommended for use by Moldovan regulatory institutions, including the National Bank of Moldova and the Ministry of Economic Development, within a real-time ensemble forecasting framework.

The interpretation of the obtained results should be grounded in the architectural features of the models under consideration. The superiority of LSTM is not accidental: its gating mechanism enables the model to selectively "remember" those periods of the past that are most informative for the current forecast. In the context of the Moldovan economy, this implies an ability to partially integrate information on price shocks and patterns of monetary transmission that MLR

1 National Bank of Moldova (NBM). Official Statistics / Interactive database. 2025. URL: https://www.bnm.md/en/content/statistics (date of access: 28.02.2026).

2 National Bureau of Statistics of the Republic of Moldova (NBS). StatBank - Statistical Databank. 2025. URL: https://statbank.statistica.md/ (date of access: 28.02.2026).

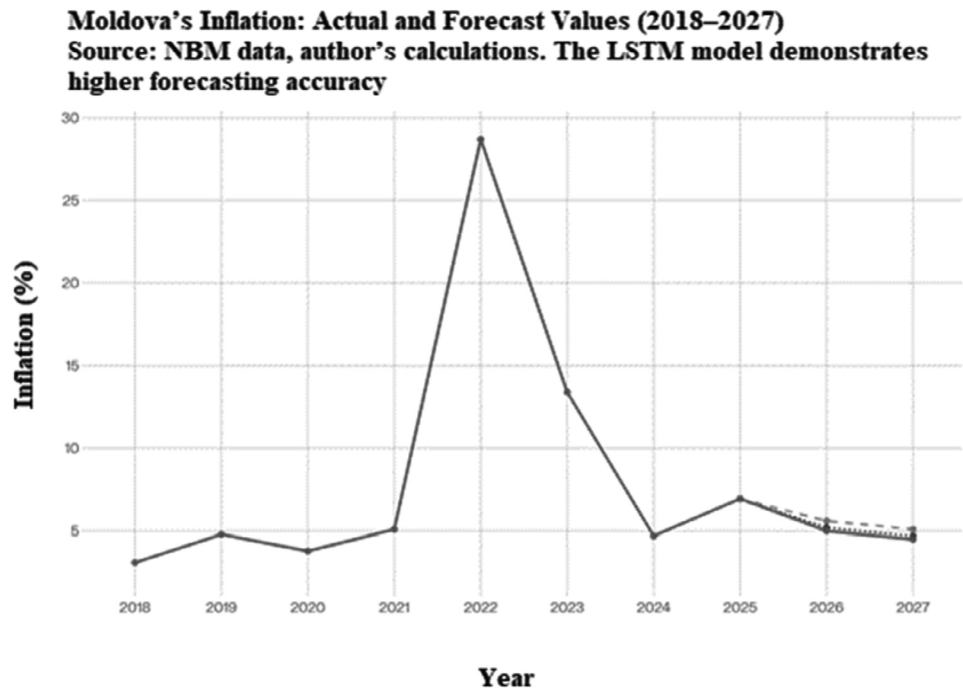

Fig. 1. Inflation Forecast for Moldova Using Three Models

and ARIMA fail to capture because of their linear nature.

At the same time, the study has several important limitations. First, the size of the training sample – 32 quarterly observations for 2018–2025 – remains at the lower threshold of adequacy for deep learning architectures. Extending the time horizon by including earlier data entails the risk of structural incomparability associated with the pre-privatization period. Second, exogenous uncertainty remains substantial: Moldova's energy dependence on external suppliers and the geopolitical instability in the region generate risks that are not determined by observable variables and therefore cannot be fully captured by any model in real time. Third, LSTM models trained on small samples are exposed to the risk of overfitting; although dropout was applied to mitigate this problem, model robustness requires further verification over an extended time horizon.

From a practical perspective, these limitations do not diminish the value of the proposed approach; rather, they define the conditions under which it should be applied.

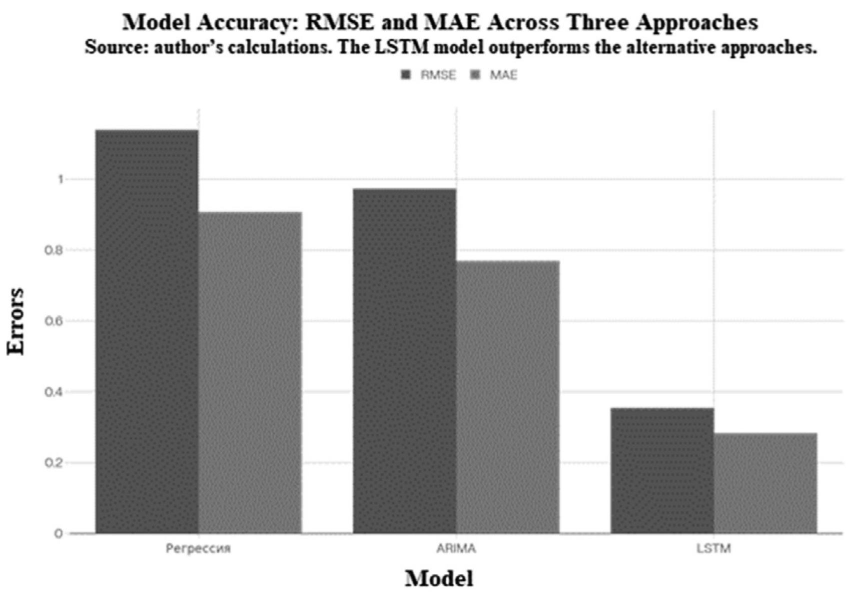

Fig. 2. Comparison of Model Accuracy by RMSE and MAE Metrics

The most appropriate format is not to replace the institutional forecast of the National Bank of Moldova with a neural-network-based one, but to employ them in parallel within an ensemble forecasting framework using weighted averaging:

$$y^{\{ens\}}_{\{t\}} = \sum\nolimits_{\{i=1\}_i}^{\{3\}w} y^{\{(i)\}}_{\{t\}},\ y^{\{(1)\}}_{\{t\}} = y^{\{REG\}}_{\{t\}},\ y^{\{(2)\}}_{\{t\}} = \; = y^{\{ARIMA\}}_{\{t\}},\ y^{\{(3)\}}_{\{t\}} = y^{\{LSTM\}}_{\{t\}},;\sum\nolimits_{\{i=1\}_i}^{\{3\}w} wi = 1 \quad . (6)$$

This approach reduces the variance of the aggregate forecasting error and increases the robustness of the forecasting system to model uncertainty.

Conclusion. The study confirmed its central hypothesis: the application of the LSTM architecture to forecasting inflation and GDP in the Republic of Moldova provides substantially higher accuracy than the classical MLR and ARIMA methods.

The reduction of RMSE to 0.354 and MAPE to 6.85% in inflation forecasting indicates the high quality of the forecast and the practical applicability of the model.

The practical significance of the results can be identified in several key areas. First, the National Bank of Moldova may use LSTM as a supplementary tool in shaping inflation expectations and calibrating the policy rate, especially during periods of heightened price volatility. Second, the Ministry of Economic Development and Digitalization gains an instrument for constructing GDP scenario forecasts with a quantitative assessment of uncertainty, which is important for medium-term budget planning. Third, the results open up prospects for the development of hybrid ensemble forecasting systems that combine the interpretability of traditional models with the adaptability of neural network architectures.

Further research should focus on extending the time horizon of the input data, incorporating high-frequency (monthly) series, and testing transformer-based architectures, including Transformer and Temporal Fusion Transformer, on Moldovan macroeconomic data.

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ШТУЧНИЙ ІНТЕЛЕКТ В ЕКОНОМІЧНОМУ АНАЛІЗІ ТА ПРОГНОЗУВАННІ РЕСПУБЛІКИ МОЛДОВА

Актуальність даного дослідження зумовлена зростаючою потребою у високоточних інструментах макроекономічного прогнозування для Республіки Молдова – невеликої відкритої економіки, яка історично дуже вразлива до зовнішніх цінових шоків, має значну залежність від імпорту енергоносіїв та характеризується постійною волатильністю реального сектора. Традиційні методи прогнозування продемонстрували свої обмеження під час останніх кризових періодів, що підкреслює потребу в більш досконалих аналітичних моделях. Метою цього дослідження є проведення всебічної порівняльної оцінки прогнозної здатності трьох різних класів моделей – множинної лінійної регресії (MLR), авторегресійної інтегрованої моделі з ковзним середнім (ARIMA) та рекурентних нейронних мереж з довгою короткостроковою пам’яттю (LSTM). Ці моделі застосовуються для прогнозування темпів інфляції та зростання валового внутрішнього продукту (ВВП) Молдови на основі макроекономічних даних за період з 2018 по 2025 рік. Емпірична інформаційна база сформована виключно на основі офіційних публікацій, наданих Національним банком Молдови (НБМ) та Національним бюро статистики Республіки Молдови. З метою забезпечення методологічної строгості якість та точність моделей оцінювалися та піддавалися перехресній валідації з використанням стандартних статистичних показників, а саме: середньоквадратичної похибки (RMSE), середньої абсолютної похибки (MAE) та середньої абсолютної процентної похибки (MAPE).

Результати порівняльного аналізу переконливо свідчать про те, що модель LSTM на основі глибокого навчання демонструє значну та стабільну перевагу над традиційною економетрикою. Зокрема, вона знижує середньоквадратичну похибку (RMSE) прогнозів інфляції з 1,139 (лінійна регресія) та 0,973 (ARIMA) до 0,354, одночасно покращуючи середньоабсолютну відхилення (MAPE) з 21,4 % та 17,3 % до надзвичайно точного показника 6,85 % відповідно. Крім того, прогноз за сценарієм на найближчий період 2026–2027 років вказує на те, що інфляція, ймовірно, стабілізується на рівні близько 5,0 % та 4,5 %, що повністю відповідає встановленому Національним банком Молдови цільовому коридору. Крім того, у базовому сценарії прогнозується стабільне зростання ВВП на рівні 2,2 % у 2026 році та 3,0 % у 2027 році. Практична цінність та новизна цього дослідження полягають у потенційній безпосередній інтеграції запропонованих прогнозних моделей на основі штучного інтелекту в стратегічні аналітичні системи Національного банку та Міністерства економічного розвитку та цифровізації Республіки Молдова, що сприятиме вдосконаленню процесу формування політики в умовах невизначеності.

Ключові слова: *Штучний інтелект, макроекономічне прогнозування, LSTM, ARIMA, Молдова.*

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The author confirms that artificial intelligence resources were used in the preparation of this manuscript. Specifically, the artificial intelligence tool Deepl was utilized for the proofreading and stylistic editing of the English text. The author takes full responsibility for the content and integrity of the published work.

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