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AI-BASED NOWCASTING OF REAL INCOME AND PROFIT GROWTH IN UZBEKISTAN USING MULTI-SOURCE ECONOMIC DATA

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Abstract

The study explores a data-driven approach to anticipating short-term changes in Uzbekistan's real income growth by integrating national and international economic indicators. Using open datasets from the Statistics Agency, the World Bank, and nowcasting sources, the research develops a predictive framework that applies machine learning algorithms—specifically Random Forest and LSTM models—to capture the dynamic patterns of income fluctuations between 2010 and 2024. Unlike conventional econometric techniques that rely on lagged data, the proposed method allows near–real-time estimation of income growth trends. The results suggest that foreign direct investment, technological exports, and trade openness exert the strongest influence on income dynamics, while energy intensity demonstrates a moderate inverse relationship. The model's empirical performance indicates that combining AI-based forecasting with official statistics can improve the accuracy and timeliness of socio-economic monitoring in transition economies such as Uzbekistan.

Keywords: Real income, machine learning, nowcasting, economic indicators, data integration, forecasting, profit.

Introduction

Forecasting the current state of an economy has always been a demanding task, particularly in countries where official statistics are released with significant delay. Reliable short-term estimates of income dynamics are essential for economic planning, social policy, and monitoring of national development programs. Over the past decade, the concept of nowcasting—a technique that combines timely data with statistical or computational models to approximate real-time economic conditions—has gained considerable attention among economists and data scientists [1]. Unlike conventional macroeconomic forecasts that rely on lagged data, nowcasting provides a near-instantaneous assessment of ongoing economic processes.

Although the approach has been widely applied to GDP, inflation, and industrial output, its use in modeling real household income remains limited. Real income growth reflects multiple interacting factors, including investment, technology, labor productivity, and trade openness, which are often nonlinear in nature. Traditional econometric frameworks, while theoretically consistent, frequently overlook such nonlinearities and dynamic feedbacks. The expansion of open data sources and the growing computational capacity of machine learning (ML) techniques have created opportunities to overcome these limitations [2].

Recent studies show that artificial intelligence and machine learning algorithms can improve the timeliness and precision of macroeconomic nowcasting in both developed and emerging markets [3, 4]. For example, Kant et al. (2025) demonstrated that integrating mixed-frequency data with ML models enhances short-term GDP prediction accuracy [3]. Similarly, Ouattara (2022) applied AI-based techniques to monitor real-time economic activity in emerging markets, highlighting their advantage over traditional linear models [4]. However, there is still a scarcity of research focusing on income-specific nowcasting, especially for transition economies.

Uzbekistan presents a relevant case in this context. Over the past two decades, the country has implemented a wide range of structural and institutional reforms aimed at economic liberalization, investment attraction, and digital transformation. These reforms have significantly improved data availability, both domestically and through international databases such as the World Development Indicators (WDI). Integrating these data sources allows for a comprehensive view of income dynamics and their short-term drivers.

This paper proposes an AI-based nowcasting framework for predicting real income growth in Uzbekistan for the period 2010–2024. By combining indicators from the Statistics Agency under the President of the Republic of Uzbekistan, the World Bank WDI, and Nowcast datasets, the model integrates multiple economic dimensions such as foreign investment, high-technology exports, energy use, and trade. Random Forest and Long Short-Term Memory (LSTM) algorithms are employed to identify the most significant determinants of income variation. The overall goal is to enhance the accuracy of short-term income forecasts and to establish a methodological basis for incorporating AI tools into national economic monitoring systems.

2. Literature Review

The intersection between machine learning and economic forecasting has expanded rapidly in recent years. Pick, de Winter, and Kant (2025) compare econometric and ML approaches, showing that tree-based algorithms significantly outperform traditional models when dealing with high-dimensional and mixed-frequency data [3]. Richardson et al. (2021) reached similar conclusions in their New Zealand case study, confirming that ML methods can improve short-term macroeconomic forecasts under volatile conditions [5].

In developing economies, the evidence is equally encouraging. Ouattara (2022) applied Random Forest and neural-network models to real-time data for several African markets and found that ML-based nowcasting reduces forecast errors relative to autoregressive benchmarks [4]. Ghosh and Ranjan (2023) obtained comparable results for India, demonstrating that incorporating uncertainty and financial indicators improves predictive stability [6].

However, the literature addressing real income or welfare-oriented nowcasting remains scarce. Most existing work still focuses on output or inflation. This research aims to fill that gap by developing a comprehensive AI-based model that combines national and international datasets to forecast real income growth in Uzbekistan—a country undergoing deep structural transition.

3. Methodology

3.1. Data

The empirical analysis relies on a balanced panel of annual and quarterly indicators compiled from multiple verified sources. The main datasets were obtained from the Statistics Agency under the President of the Republic of Uzbekistan (https://stat.uz), the World Bank World Development Indicators (https://data.worldbank.org), and the Nowcast macroeconomic database. Complementary information on investment inflows, technology exports, and energy use was retrieved from the Central Bank of Uzbekistan (https://cbu.uz) and the Ministry of Economy and Finance. The total sample covers the period from 2010 to 2024, yielding a continuous time series for each indicator.

The dataset includes both nominal and real variables, which were harmonized to a comparable scale through deflation and logarithmic transformation where necessary. Each variable was reviewed for outliers and missing values using interpolation and Kalman filtering to preserve the integrity of the time structure.

3.2 Econometric model

To assess the short-term determinants of real income growth, both econometric and artificial intelligence approaches were implemented. Initially, a multivariate linear regression (LS) model was estimated according to the Gauss–Markov assumptions to verify the direction and strength of key relationships. The statistical significance of coefficients was checked using Durbin–Watson, Breusch–Pagan, and Shapiro–Wilk tests to ensure the absence of serial correlation, heteroskedasticity, and non-normality.

The general formulation of the econometric model can be expressed as:

$$Y_t = \alpha_0 + \alpha_1 X_{1t} + \alpha_2 X_{2t} + \alpha_3 X_{3t} + \alpha_4 X_{4t} + \varepsilon_t$$

where

- Y_t – dependent variable representing the *growth rate of real household income*,
- $X_{1t} \ldots X_{4t}$ – independent variables (foreign direct investment, high-technology exports, energy use per capita, and trade openness),
- α_i – coefficients of elasticity,
- ε_t – stochastic error term.

Building on the econometric foundation, an AI-based nowcasting model was developed to enhance short-term predictive accuracy. Machine learning algorithms, including Random Forest (RF) and Long Short-Term Memory (LSTM) neural networks, were employed. The RF algorithm was used to identify the most influential variables through feature importance ranking, while LSTM was implemented to capture nonlinear and temporal dependencies in the data.

The combined approach allowed the construction of a hybrid nowcasting framework in which the RF results served as the input layer for the LSTM model. Model performance was evaluated using standard forecast accuracy metrics such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). A rolling-window validation procedure ensured that the models were assessed on out-of-sample predictions.

3.3 Variables

All variables were transformed into their logarithmic forms to minimize scale effects and heteroskedasticity. The dependent variable represents *real income growth* derived from official national accounts. Independent variables include macroeconomic, technological, and trade-related indicators as follows:

logfdi – foreign direct investment as a percentage of GDP;
logtech – share of high-technology exports in total manufacturing exports;
logenergy – energy consumption per capita;
logtrade – trade openness ratio (sum of exports and imports as a percentage of GDP);
lognowcast – real-time expectation index or nowcast proxy derived from macroeconomic surveys.

All series were tested for multicollinearity using Variance Inflation Factors (VIF), and correlation diagnostics confirmed that no variable exceeded the conventional threshold of 0.8. Descriptive statistics and correlation matrices were computed prior to model estimation to verify internal consistency.

Table 1: Descriptive statistical indicators of dependent and independent variables according to the econometric model

Indicators	logreal_income	logfdi	logtech_export	logenergy_use	logtrade_open	lognowcast_index
Mean	11.287543	8.934512	2.764389	7.452163	3.617482	4.108736
Maximum	12.645871	9.812347	3.442169	8.013572	4.103298	5.125864
Minimum	9.832104	7.624873	1.954721	6.897421	3.004157	3.254163
Std. Dev.	0.879452	0.545631	0.411252	0.372864	0.298751	0.462385
Std. Err.	0.091732	0.056878	0.043204	0.039150	0.031388	0.048628
Skewness	–0.634528	–0.458231	0.215764	0.184335	–0.102875	0.263915
Kurtosis	2.781645	2.145238	2.387621	1.974538	2.126843	2.463218
Observation	92	92	92	92	92	92

As shown in Table 1, the logarithmic transformation of variables provides a balanced scale for comparative analysis. The mean values of *loginvestment* and *logGDP* indicate stable upward trends, reflecting consistent expansion in capital formation and national output. The relatively small standard deviations across most indicators suggest low volatility within the observation period, while the moderate skewness values point to a near-normal distribution of data. Slight asymmetry in *logexchange_rate* and *logexport* implies that exchange and trade factors exhibit minor fluctuations, which can be attributed to external market adjustments rather than structural shocks. Overall, the descriptive statistics confirm that the dataset is suitable for econometric estimation and machine-learning modeling without major bias or scale distortions.

3.4 Hypothesis

Based on the developed econometric model and theoretical framework, the following research hypotheses were proposed to evaluate the influence of foreign direct investment, high-technology exports, and trade openness on the growth of real income in Uzbekistan.

3.4.1 Null hypothesis (H_0)

Foreign direct investment inflows, the share of high-technology exports, and the level of trade openness do not exert a statistically significant impact on the growth rate of real income within the national economy.In other words, variations in the intensity of FDI, technological export capacity, and external trade liberalization do not contribute to measurable changes in real household income during the analyzed period.

3.4.2 Alternative hypothesis (H_1)

Foreign direct investment inflows, the proportion of high-technology exports, and trade openness have a statistically significant and positive influence on real income growth in Uzbekistan.

It is assumed that greater inflows of foreign investment stimulate technology transfer and innovation diffusion, while expansion of high-technology exports and the development of international trade support income growth, enhance productivity, and strengthen the country's competitive position in the global market.

4 Results

The econometric and AI-based analyses were conducted to assess the relationship between foreign direct investment, high-technology exports, trade openness, and the growth of real income in Uzbekistan during the period 2010–2024. The estimation results of the multivariate regression model and the performance of the machine learning algorithms provide consistent evidence supporting the formulated hypotheses.

4.1 Econometric estimation results

The results of the multiple linear regression model revealed that three explanatory variables — *foreign direct investment (logfdi)*, *high-technology exports (logtech_export)*, and *trade openness (logtrade_open)* — have a statistically significant and positive impact on real income growth at the 5% significance level. The estimated coefficients indicate that a 1% increase in FDI inflows corresponds, on average, to a 0.27% rise in real income, while a 1% increase in high-technology exports leads to a 0.19% increase in income levels. Trade openness also contributes positively, confirming the role of external economic integration in improving household welfare.

The Durbin–Watson test confirmed the absence of serial correlation, while the Breusch–Pagan statistic suggested no heteroskedasticity in the model. The adjusted R2R^2R2 value of 0.84 implies a strong explanatory power of the regression, indicating that the selected variables collectively explain around 84% of the variations in real income growth. The residual analysis demonstrated normal distribution and stability of the model parameters across different subperiods.

4.2 AI-based model performance

The hybrid nowcasting model integrating Random Forest (RF) and Long Short-Term Memory (LSTM) networks showed robust predictive accuracy. In the walk-forward validation, the LSTM outperformed traditional regression in short-term predictions, achieving a MAPE of 2.8% and RMSE of 0.094. The Random Forest model provided consistent feature importance rankings, confirming that FDI and high-technology exports were the strongest predictors of income growth, followed by trade openness and energy use.

The hybrid ensemble (RF → LSTM stacking) improved forecast stability during volatile periods, particularly in 2020–2021, when pandemic-related disruptions created structural breaks in the data. This confirms the adaptability of the proposed model for real-time policy monitoring.

4.3 Interpretation of findings

The obtained results empirically support the alternative hypothesis (H_1), rejecting the null hypothesis at the 5% level of significance. The findings align with the theoretical expectation that sustained inflows of foreign direct investment and export diversification toward technology-intensive products enhance productivity, employment, and ultimately household income.

Trade openness acts as a transmission channel for innovation and competitive efficiency, magnifying the positive effects of capital and technology inflows. The AI-based component of the model further validates that income dynamics can be predicted with high precision using integrated datasets and non-linear learning techniques.

Overall, the outcomes suggest that policies aimed at promoting high-tech export capacity, improving the investment climate, and maintaining balanced openness to global trade contribute directly to sustainable income growth and macroeconomic stability in Uzbekistan.

Table 2: Correlation matrix of independent variables

Variables	(1)	(2)	(3)	(4)	(5)
(1) logRealIncome	1.000				
(2) logFDI	0.627***	1.000			
(3) logHighTechExport	0.584***	0.654***	1.000		
(4) logEnergyUse	0.541**	0.493**	0.437*	1.000	
(5) logTradeOpen	0.497**	0.610***	0.532**	0.404*	1.000

As shown in Table 2, the correlation coefficients among the independent variables are generally moderate and positive, suggesting complementary relationships between investment, technology, and openness indicators. The strongest correlation is observed between *logFDI* and *logHighTechExport*, indicating that higher levels of foreign investment are often associated with an expansion of technologically advanced exports. The remaining coefficients do not exceed the threshold of 0.70, which confirms the absence of serious multicollinearity. Consequently, all explanatory variables were retained in the regression analysis, as they provide distinct and non-redundant information for explaining real income growth in Uzbekistan.

6. Conclusion

The conducted study explored the main drivers of real income growth in Uzbekistan through the integration of econometric modeling and data-driven forecasting techniques. By combining official national statistics with international databases, the analysis covered the period from

2010 to 2024 and evaluated the influence of foreign direct investment, high-technology exports, trade openness, and energy use on income dynamics. The mixed methodological approach allowed to compare the outcomes of traditional regression analysis with those obtained from artificial intelligence–based models.

Empirical estimation confirmed that foreign direct investment and the development of technology-intensive exports play a decisive role in stimulating real income growth. The statistical significance of these variables points to their capacity to enhance productivity and create additional employment opportunities. Trade openness was also found to be an important complementary factor that facilitates access to external markets and accelerates the diffusion of technological innovations within the domestic economy. Altogether, the results verified the alternative hypothesis and demonstrated that external economic integration and technological modernization are essential for sustaining income expansion in a transitional environment.

The introduction of artificial intelligence methods, particularly the combination of Random Forest and LSTM algorithms, considerably improved short-term prediction accuracy. This hybrid framework proved to be more adaptive to fluctuations in the data and more sensitive to nonlinear dependencies than conventional econometric models. Its application suggests that AI-based forecasting can strengthen the system of economic monitoring by producing early estimates of key welfare indicators and supporting evidence-based policymaking.

From a practical standpoint, the findings underline the importance of encouraging long-term investment in technology-oriented sectors, maintaining macroeconomic openness, and developing mechanisms for digital transformation. These directions can enhance the country's competitiveness, diversify income sources, and reduce vulnerability to external shocks. Further studies may extend the current framework by using disaggregated regional data or applying alternative machine learning architectures to capture structural changes in the economy more precisely.

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