
RESEARCH ARTICLE**Application of Artificial Intelligence Models in Predicting Oil Price Volatility and Its Impact on Nigeria's Economic Growth****Kamaluddeen Musa Yashi¹✉, Abdulrahman Mohammed², Meriji Morgan³ and Aminu Adamu Ahmed⁴**¹ *Department of Science Laboratory Technology, Nigerian Building and Road Research Institute, Gombe State, Nigeria*² *Department of Computer Science, Federal Polytechnic Kaltungo, Gombe State, Nigeria*³ *Department of Business Administration and Management, Federal Polytechnic Kaltungo, Gombe State, Nigeria*⁴ *Department of Information and Communication Technology, Federal Polytechnic Kaltungo, Gombe***Corresponding Author:** Aminu Adamu Ahmed, **E-mail:** aaahmed.pg@atbu.edu.ng**ABSTRACT**

Oil price volatility constitutes the primary source of macroeconomic instability in Nigeria, a petroleum-dependent economy where crude oil accounts for 87% of export earnings and 68% of government revenue. Conventional econometric models – ARIMA, GARCH, and VAR have demonstrated persistent limitations in capturing the nonlinear, structurally asymmetric dynamics of contemporary global oil markets. This study develops, benchmarks, and validates five AI-based forecasting models: LSTM-GARCH hybrid, Bidirectional LSTM, Temporal Fusion Transformer (TFT), XGBoost with SHAP interpretability, and a stacked ensemble using daily oil price and macro-financial data spanning 2000–2024 (N = 6,008 observations). The stacked ensemble achieved the lowest RMSE (1.51), MAPE (2.63%), and highest directional accuracy (83.7%), significantly outperforming all econometric baselines (Diebold-Mariano $p < 0.001$). ARDL bounds testing confirms long-run cointegration between oil price volatility and Nigeria's GDP growth, exchange rate, inflation, and government revenue. Long-run ARDL estimates reveal that a one standard deviation increase in oil price volatility reduces Nigeria's real GDP growth by 0.342 percentage points ($p < 0.001$) while raising exchange rate depreciation by 0.584 percentage points and inflation by 0.463 percentage points. Time-varying parameter VAR (TVP-VAR) analysis demonstrates that the macroeconomic impact of oil price shocks is asymmetric negative shocks generate contractions 1.37 to 1.81 times larger than expansions generated by equivalent positive shocks and that the transmission intensity has strengthened post-2015. These findings carry profound implications for Nigeria's fiscal planning, monetary policy, and sovereign wealth management, and establish AI-based price forecasting as an essential tool for evidence-based economic governance in oil-dependent developing economies.

KEYWORDS

Artificial Intelligence; Oil Price Volatility; LSTM; Temporal Fusion Transformer; Nigeria; GDP; ARDL; TVP-VAR; Economic Growth; Energy Economics.

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1. Introduction

Nigeria's macroeconomic trajectory is inextricably bound to the global oil price cycle. The country's heavy petroleum dependence – crude oil constitutes approximately 87% of foreign exchange earnings and 68% of consolidated government revenue (NBS, 2024; CBN, 2023) – means that oil price volatility functions as a powerful amplifier of fiscal and monetary instability. The naira's exchange rate, the federal government's annual budget benchmark, the Central Bank of Nigeria's (CBN) interest rate decisions, and the country's foreign reserve adequacy all exhibit strong sensitivity to oil price movements (Ogundipe et al., 2022; Alley et al., 2023). Between 2000 and 2024, Nigeria experienced three severe oil price-driven recessions (2008–2009,

2015–2016, 2020), with cumulative GDP losses estimated at over \$180 billion in present value terms (World Bank, 2024; IMF, 2024).

The tools available to Nigerian policymakers for anticipating oil price movements have historically been inadequate. The Federal Ministry of Finance relies primarily on OPEC projections and World Bank commodity outlooks for setting annual budget oil price benchmarks, approaches that consistently underperform sophisticated statistical forecasts (Nwosu & Igwe, 2022). Between 2015 and 2023, Nigeria's actual oil revenue deviated from budgeted projections by an average of 34.7% per annum – a divergence that necessitated emergency borrowing, mid-year budget revisions, and the drawdown of sovereign reserves in multiple fiscal years (FIRS, 2023). This persistent forecasting underperformance constitutes a systemic governance failure with direct implications for national development financing, debt sustainability, and economic stability.

The emergence of AI forecasting architectures – including LSTM networks, Transformer-based models, and ensemble machine learning systems – has opened new possibilities for commodity price prediction that transcend the structural limitations of conventional econometric approaches. These AI models can capture nonlinear dependencies, accommodate regime shifts and structural breaks, and incorporate high-dimensional predictor sets including satellite data, shipping traffic, geopolitical risk indices, and financial market sentiment without the distributional assumptions that constrain ARIMA and GARCH specifications (Jabeur et al., 2023; Liang et al., 2024; Zhu et al., 2024). However, despite a growing global literature on AI-based oil price forecasting, there remains a critical scarcity of studies that: (i) provide multi-architecture AI model benchmarks calibrated to Nigeria's Bonny Light crude oil exposure; (ii) translate AI-generated volatility forecasts into quantitative macroeconomic impact estimates for the Nigerian economy; and (iii) derive policy-relevant conclusions for Nigerian fiscal and monetary management.

This paper directly addresses these gaps. Using a comprehensive dataset of 6,008 daily observations spanning 2000–2024, we develop and benchmark five AI forecasting architectures against econometric baselines and subsequently deploy the best-performing models as inputs to ARDL bounds testing and TVP-VAR macroeconomic impact analysis. The paper's contributions are: (1) the first comprehensive multi-architecture AI oil price volatility benchmarking study for the Nigerian market context; (2) novel TVP-VAR evidence on the time-varying and asymmetric transmission of oil price volatility to Nigeria's macroeconomic aggregates; and (3) actionable policy frameworks for integrating AI forecasting into Nigeria's fiscal and monetary governance architecture.

2. Literature Review

2.1 Theoretical Foundations

The theoretical basis for oil price volatility's macroeconomic impact in petroleum-dependent economies is grounded in the Dutch Disease and Resource Curse frameworks. Corden & Neary (1982) established the canonical Dutch Disease model showing how oil revenue windfalls cause exchange rate appreciation and de-industrialisation; Sachs & Warner (1995) and van der Ploeg (2021) extended these insights to the volatility dimension, demonstrating that price uncertainty compounds the misallocation effects of resource dependence. Kilian (2009) provided the seminal empirical decomposition of oil price movements into supply shocks, aggregate demand shocks, and oil-market-specific demand shocks, establishing an analytical framework that continues to structure empirical research. Hamilton (2009) documented the macroeconomic consequences of oil price shocks across multiple historical episodes, confirming their persistent contractionary effects.

2.2 Conventional Econometric Models for Oil Price Forecasting

Baumeister & Kilian (2022) conducted a comprehensive evaluation of oil price forecasting models, including random walk benchmarks, ARIMA, VAR, and BVAR specifications, finding that no single approach consistently dominates across forecast horizons. GARCH-family models – including EGARCH (Nelson, 1991), DCC-GARCH (Engle, 2002), and FIGARCH – have been widely applied to oil price volatility modelling, with Antonakakis et al. (2023) demonstrating that DCC-GARCH frameworks effectively capture spillovers between oil price volatility and equity markets. However, all GARCH specifications assume that conditional variance follows a parametric functional form, a restriction that AI models circumvent through data-driven nonlinear approximation.

2.3 AI Models for Oil Price Volatility Prediction

The AI forecasting literature for oil prices has grown substantially since 2019. Jabeur et al. (2023) compared LSTM, GRU, and TFT models against ARIMA-GARCH benchmarks for Brent crude price prediction, finding that TFT achieved the lowest MAPE of 2.89% over a 30-day horizon. Liang et al. (2024) applied a hybrid CNN-LSTM architecture incorporating news sentiment indices, reporting a 34% reduction in RMSE relative to GARCH benchmarks. Fang et al. (2023) demonstrated that XGBoost with SHAP interpretability provided superior risk-adjusted forecasting for WTI crude during the COVID-19 period. Zhu et al. (2024) showed that ensemble stacking consistently outperformed individual AI models in directional accuracy for oil price prediction. In the

African context, Adekunle & Salami (2023) applied LSTM models to West African crude prices with MAPE of 3.8%, while Abubakar et al. (2024) found that GARCH-LSTM hybrids outperformed pure specifications for Bonny Light crude in Nigeria.

2.4 Oil Price Volatility and Nigeria's Macroeconomy

The macroeconomic literature on oil price–Nigeria linkages is extensive. Olomola & Adejumo (2006) established a significant negative impact of oil price volatility on Nigeria's real exchange rate. Ogundipe et al. (2022), using a VAR model over 1990–2020, found asymmetric transmission: a one standard deviation positive oil price shock raises Nigeria's GDP by 0.87 percentage points, while an equivalent negative shock contracts GDP by 1.34 percentage points. Nwosu & Igwe (2022) used ARDL bounds testing to establish long-run cointegration between oil price volatility, government expenditure, and inflation. Alley et al. (2023) applied TVP-VAR to document intensifying exchange rate pass-through from oil price shocks post-2015. Babatunde et al. (2024) estimated that improved oil revenue forecasting precision could save Nigeria's government N847 billion annually in emergency borrowing costs. These studies collectively motivate this paper's integrated AI forecasting and macroeconomic impact framework.

3. Methodology

3.1 Dataset

The study uses daily data spanning January 2000 to December 2024 (N = 6,008 observations after alignment and cleaning), compiled from multiple sources. Oil price series (Brent crude spot price in USD/barrel) and US EIA weekly petroleum inventory data were obtained from the US Energy Information Administration. Nigeria-specific Bonny Light crude prices and NNPC production volumes were obtained from NNPC's monthly oil market reports. Macroeconomic variables – quarterly real GDP growth, monthly headline inflation, and monthly government oil revenue – were obtained from NBS and the CBN Statistical Bulletin. The daily NGN/USD exchange rate series was obtained from the CBN and Bloomberg Terminal. The Geopolitical Risk (GPR) Index was sourced from Caldara & Iacoviello (2022). The VIX (CBOE Volatility Index) and US Dollar Index (DXY) were obtained from Bloomberg. OPEC production compliance data were sourced from the OPEC Secretariat Monthly Oil Market Reports. Table 1 presents descriptive statistics.

Table 1: Descriptive Statistics of Key Variables (Daily Data, 2000–2024, N = 6,008)

Variable	Mean	Std Dev	Min	Max	Skew	Obs.
Brent Crude (USD/bbl)	71.34	27.81	19.33	127.98	0.41	6,008
Realised Volatility (σ)	0.284	0.142	0.042	0.891	1.73	6,008
Nigeria GDP Growth (%)	2.87	3.42	−1.82	8.01	−0.38	96
Exchange Rate (NGN/USD)	468.7	324.2	117.0	1,580	1.21	6,008
Geopolitical Risk Index	118.4	64.7	48.2	387.1	1.84	6,008
Global Demand Index	102.3	8.41	68.7	121.4	−0.62	6,008
VIX (Financial Stress)	19.84	9.72	9.14	82.69	2.31	6,008
OPEC Compliance (%)	91.4	14.8	48.0	116.0	−0.74	6,008

Note: DA = Directional Accuracy. σ = Realised volatility computed as 22-day rolling standard deviation of log returns. GDP growth at quarterly frequency (N = 96). Source: EIA, NBS, CBN, Bloomberg.

3.2 AI Model Development

Five AI model architectures were developed and benchmarked. (i) LSTM-GARCH Hybrid: A 2-layer LSTM with 64 hidden units whose outputs fed into a GARCH(1,1) volatility equation, exploiting the LSTM's nonlinear sequence modelling capacity alongside GARCH's established volatility clustering representation. (ii) Bidirectional LSTM (BiLSTM): A dual-direction LSTM processing oil price sequences in both forward and reverse temporal directions, capturing long-range dependencies that unidirectional models may miss. (iii) Temporal Fusion Transformer (TFT): A multi-head attention Transformer with variable selection networks, temporal self-attention, and quantile regression outputs for uncertainty-calibrated multi-horizon volatility forecasting. (iv) XGBoost-SHAP: An extreme gradient boosting model with 500 estimators, maximum depth 6, learning rate 0.03, and post-hoc SHAP explainability analysis. (v) Stacked Ensemble: A two-level ensemble combining predictions from all four base models via a logistic regression meta-learner trained on a hold-out validation set.

All models were trained on 2000–2018 data (N = 4,713 observations), validated on 2019–2021 data (N = 784), and tested on 2022–2024 data (N = 511). Input features encompassed: lagged oil price returns (1, 5, 22, 65 days), realised volatility measures, technical indicators (RSI, Bollinger Bands, MACD), OPEC compliance index, VIX, DXY, geopolitical risk index, and global demand index. Hyperparameters were optimised via Bayesian search using Optuna v3.5. Model comparison used the Diebold-Mariano

(DM) test with Harvey, Leybourne & Newbold (HLN) small-sample correction, testing each AI model against the best-performing econometric baseline (VAR).

3.3 Macroeconomic Impact Analysis

Two complementary econometric frameworks assessed oil price volatility's macroeconomic transmission. First, ARDL bounds testing (Pesaran et al., 2001) was applied to estimate long-run cointegrating relationships and error correction dynamics between oil price volatility and Nigeria's key macroeconomic indicators (GDP growth, exchange rate, inflation, government revenue, foreign reserves) over 2000Q1–2024Q4 (quarterly data, $N = 96$ after temporal aggregation). The optimal ARDL lag structure was determined via the Akaike Information Criterion (AIC). Second, a Time-Varying Parameter VAR (TVP-VAR) model (Nakajima, 2011; Koop & Korobilis, 2013) was estimated to capture how the macroeconomic transmission of oil price shocks has evolved across the study period, allowing impulse response functions to vary with the prevailing macroeconomic and policy regime. The TVP-VAR was estimated using Markov Chain Monte Carlo (MCMC) simulation with 10,000 draws (2,000 burn-in).

4. Results and Discussion

4.1 AI Model Forecasting Performance

Table 2 presents the comparative forecasting performance of all AI models and econometric baselines on the 2022–2024 test set. The stacked ensemble achieved the best performance across all metrics: RMSE of 1.51, MAPE of 2.63%, R^2 of 0.973, and directional accuracy of 83.7%. The TFT ranked second (RMSE 1.64, MAPE 2.89%, DA 81.4%), followed by the LSTM-GARCH hybrid (RMSE 1.82, MAPE 3.14%). All AI models significantly outperformed the VAR baseline (RMSE 3.27, MAPE 5.14%, DA 65.2%), with Diebold-Mariano statistics ranging from 3.42 to 6.14 (all $p < 0.001$). The XGBoost-SHAP model, while less accurate than neural architectures in point forecasting, provided the highest interpretability: SHAP analysis identified the 22-day realised volatility (mean $|SHAP| = 0.347$), VIX (0.218), OPEC compliance (0.187), and geopolitical risk index (0.142) as the four dominant predictors of oil price volatility.

Table 2: Comparative AI and Econometric Model Forecasting Performance (Test Set: 2022–2024)

Model	RMSE	MAE	MAPE (%)	R^2	DA (%)	DM Stat.
ARIMA (Baseline)	3.84	2.97	6.21	0.879	61.4	—
GARCH(1,1) (Baseline)	3.41	2.64	5.48	0.901	63.7	—
VAR (Baseline)	3.27	2.51	5.14	0.912	65.2	—
LSTM-GARCH Hybrid	1.82	1.41	3.14	0.954	78.3	4.21***
Bidirectional LSTM	2.07	1.63	3.67	0.941	76.1	3.87***
Temporal Fusion Transformer	1.64	1.27	2.89	0.968	81.4	5.63***
XGBoost-SHAP	2.31	1.84	4.12	0.927	74.8	3.42***
Stacked Ensemble	1.51*	1.18*	2.63*	0.973*	83.7*	6.14***

Note: * Best-performing model. *** $p < 0.001$ (DM test vs. VAR baseline). DA = Directional Accuracy (%). Orange = econometric baselines; Green = best AI model. Source: Authors' computations.

4.2. ARDL Bounds Test and Long-Run Elasticities

Table 3 presents ARDL bounds test results for five macroeconomic dependent variables. F-statistics for all five models exceed the 5% upper bound critical value (4.01), confirming long-run cointegration between oil price volatility and each macroeconomic indicator. The error correction term (ECT) coefficients in Table 4 are all negative and statistically significant (ranging from -0.291 to -0.447), indicating that deviations from long-run equilibrium are corrected within 2.2 to 3.4 quarters – consistent with the quarterly oil revenue disbursement cycle of Nigeria's federation account.

Table 3: ARDL Bounds Test Results for Long-Run Cointegration

Dependent Variable	F-Statistic	I(0) Bound (5%)	I(1) Bound (5%)	Decision
GDP Growth (Δgdp)	7.841***	2.86	4.01	Cointegrated
Exchange Rate (Δexr)	9.213***	2.86	4.01	Cointegrated
Inflation Rate (Δinf)	6.542***	2.86	4.01	Cointegrated
Government Revenue (Δrev)	8.174***	2.86	4.01	Cointegrated
Foreign Reserves (Δres)	5.896**	2.86	4.01	Cointegrated

Note: *** $p < 0.001$; ** $p < 0.01$. Critical values from Pesaran et al. (2001), Table CI(iii). Optimal lags selected by AIC.

Table 4: Long-Run ARDL Elasticity Estimates (Normalised Coefficients)

Variable (Regressor)	GDP Growth	Exch. Rate	Inflation	Gov't Revenue
Oil Price Level (log)	0.487***	−0.612***	−0.341***	0.728***
Oil Price Volatility (σ)	−0.342***	0.584***	0.463***	−0.519***
Global Demand Index	0.214**	−0.187**	−0.142*	0.261**
Geopolitical Risk	−0.118*	0.231**	0.187**	−0.143*
Exchange Rate (log)	−0.274***	—	0.381***	−0.312***
ECT (t-1)	−0.384***	−0.412***	−0.291***	−0.447***
Adj. R ²	0.742	0.804	0.718	0.831

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. ECT = Error Correction Term. HC3 standard errors. Source: Authors' ARDL estimates (2000Q1–2024Q4).

The long-run ARDL elasticities in Table 4 reveal that oil price volatility (σ) exerts significant negative effects on GDP growth ($\beta = -0.342$, $p < 0.001$) and government revenue ($\beta = -0.519$, $p < 0.001$), while generating significant positive effects on exchange rate depreciation ($\beta = 0.584$, $p < 0.001$) and inflation ($\beta = 0.463$, $p < 0.001$). In contrast, the oil price level itself exerts positive effects on GDP and government revenue, underscoring the distinction between oil price level effects (broadly positive) and oil price volatility effects (broadly negative) – a finding consistent with the uncertainty-investment suppression mechanism documented by Bloom (2009).

4.3 TVP-VAR: Time-Varying Macroeconomic Transmission

Table 5 presents the cumulative GDP impulse responses to a positive one-standard-deviation oil price shock across four major episodes. The results confirm substantial time-variation in the macroeconomic transmission of oil price shocks. During the 2014–2016 oil price bust, a positive price shock generated a cumulative eight-quarter GDP uplift of 0.93 percentage points, while the 2022 Russia-Ukraine surge episode produced the strongest cumulative response of 1.38 percentage points – reflecting both the heightened fiscal sensitivity of Nigeria's economy following the 2016 recession and the improved oil production recovery post-COVID.

Table 5: TVP-VAR Cumulative GDP Impulse Responses to $+1\sigma$ Oil Price Shock (Selected Episodes).

Response of GDP to Oil Price Shock ($+1\sigma$)	2008–2010 Crisis	2014–2016 Bust	2020 COVID	2022 Surge
Quarter 1 (cumulative)	+0.28%	+0.41%	+0.19%	+0.52%
Quarter 2 (cumulative)	+0.54%	+0.87%	+0.33%	+0.94%
Quarter 4 (cumulative)	+0.72%	+1.12%	+0.41%	+1.38%
Quarter 8 (cumulative)	+0.61%	+0.93%	+0.29%	+1.14%
Asymmetry: Negative Shock Multiplier	1.42×	1.74×	1.81×	1.37×

Note: Asymmetry multiplier = $|GDP \text{ response to } -1\sigma \text{ shock}| / |GDP \text{ response to } +1\sigma \text{ shock}|$. Source: Authors' TVP-VAR estimates.

The asymmetry multiplier (Table 5, final row) consistently exceeds unity across all episodes, ranging from 1.37 (2022 surge) to 1.81 (2020 COVID), confirming that negative oil price shocks generate contractionary effects 37–81% larger in magnitude than expansions produced by equivalent positive shocks. This asymmetry is most pronounced during the 2020 COVID episode, when the combination of price collapse and demand destruction simultaneously suppressed all channels of macroeconomic adjustment.

4.4 Policy Implications

The findings of this study generate five concrete policy recommendations. First, the Federal Ministry of Finance should integrate the stacked ensemble AI forecasting model – which demonstrated 83.7% directional accuracy and 2.63% MAPE – into Nigeria's annual budget oil price benchmarking process, replacing the current consensus-based approach. Econometric simulation indicates that reducing the annual oil revenue forecast deviation from the current 34.7% average to the AI-model-implied 8.2% would save Nigeria approximately N847 billion annually in emergency borrowing and mid-year supplementary appropriation costs (Babatunde et al., 2024).

Second, the Central Bank of Nigeria should deploy AI-based oil price volatility forecasts as early warning inputs into its foreign exchange reserve management framework, enabling counter-cyclical reserve accumulation during AI-predicted high-price periods to buffer against subsequent volatility episodes. Third, the Nigeria Sovereign Investment Authority (NSIA) should use AI-

generated multi-horizon oil price scenarios to calibrate the allocation between the Stabilisation Fund, the Future Generations Fund, and the Nigeria Infrastructure Fund – optimising the inter-temporal smoothing of oil revenue volatility. Fourth, the Nigerian government should accelerate fiscal diversification reforms to reduce the economy's GDP elasticity to oil price volatility, targeting a reduction in the estimated -0.342 long-run elasticity through expanded non-oil tax revenue mobilisation. Fifth, the adoption of AI oil price forecasting tools should be institutionalised through capacity building at the CBN Research Department, the Fiscal Responsibility Commission, and the Office of the Accountant-General.

5. Conclusion

The findings of this study contribute to the literature on artificial intelligence, energy economics, and macroeconomic forecasting in three key ways. First, the study provides strong empirical evidence that AI-based forecasting models significantly outperform traditional econometric approaches in predicting oil price volatility. Using 6,008 daily observations, the results show that the stacked ensemble model achieved the best performance (RMSE: 1.51, MAPE: 2.63%, Directional Accuracy: 83.7%), followed closely by the Temporal Fusion Transformer (RMSE: 1.64, MAPE: 2.89%). These results confirm that machine learning and deep learning methods are more effective in capturing the nonlinear and dynamic behavior of global oil markets compared to conventional models such as ARIMA, GARCH, and VAR.

Second, the study provides important insights into the macroeconomic effects of oil price volatility in Nigeria. Using ARDL bounds testing and TVP-VAR analysis, the results show that oil price fluctuations have persistent and asymmetric impacts on the economy. Specifically, volatility negatively affects long-run economic growth and government revenue, while also contributing to exchange rate depreciation and rising inflation. These findings highlight Nigeria's structural dependence on oil revenues and emphasize the need for stronger macroeconomic stabilization policies and economic diversification.

Third, the study demonstrates the practical value of AI-based forecasting for policy formulation. Integrating real-time AI predictions into fiscal planning, monetary policy, sovereign wealth management, and risk assessment can improve budget accuracy, strengthen foreign exchange management, and enhance inflation control. It also enables policymakers to respond more effectively to external oil shocks.

Overall, the study shows that artificial intelligence is not only a technological advancement but also a strategic tool for improving economic resilience in resource-dependent economies. As global energy markets become more volatile due to geopolitical tensions, technological change, and climate policies, AI-based forecasting will play an increasingly important role in economic planning. Future research should incorporate alternative data sources such as satellite imagery, social media sentiment, geopolitical risk indicators, and climate transition variables to further improve forecasting accuracy and deepen understanding of oil price dynamics and their economic implications.

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