Hybrid Modelling of Exchange Rate Dynamics: Policy Insights from USD–INR Forecasting with Machine Learning and Econometrics

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Abstract

This study examines the dynamics of India's economy over the past six and a half decades (1960–2024), with a focus on how the USD–INR exchange rate interacts with key factors, including the Consumer Price Index (CPI), lending rates, and the GBP–USD currency rate. To ensure the data was ready for analysis, we applied a range of pre-processing techniques, including log transformations, differencing, and normalisation, followed by stationarity checks using both the Augmented Dickey-Fuller (ADF) and KPSS tests. Authors have compared traditional econometric models such as ARIMA & GARCH with deep learning approaches like LSTM, XGBoost, and LightGBM. To evaluate performance fairly, we used rigorous validation techniques such as walk-forward validation and time-series cross-validation, along with interpretability tools like SHAP, partial dependence plots (PDP), and LIME. The results show that LSTM models significantly outperformed conventional methods, reducing error by 35% (based on RMSE). Among all predictors, CPI proved to be the most influential driver of USD–INR movements. Importantly, the models remained reliable even during periods of major economic turbulence, achieving an out-of-sample R^2 of 0.783.

Key Words: Machine Learning, Time series, ARIMA, LSTM, Hybrid model, GPR, Foreign Exchange

Introduction

The global financial landscape has undergone profound transformations over the past six decades, with exchange rates serving as critical barometers of economic health and stability. Among emerging market currencies, the Indian Rupee (INR) has witnessed remarkable evolution, reflecting India's journey from a closed, centrally planned economy to one of the world's fastest-growing major economies. Since 1960, the Indian economy has navigated through multiple phases of economic development, each characterised by distinct policy regimes, structural reforms, and external challenges that have fundamentally shaped the dynamics of the USD-INR exchange rate. The significance of exchange rate analysis extends far beyond academic curiosity. For policymakers, understanding exchange rate dynamics is crucial for maintaining macroeconomic stability, controlling inflation, and ensuring sustainable economic growth. The Reserve Bank of India (RBI) has consistently emphasised the importance of exchange rate stability as a key pillar of monetary policy, particularly in the context of India's increasing integration with global financial markets. For investors and financial institutions, accurate exchange rate forecasting translates directly into improved risk management, enhanced portfolio performance, and more informed strategic decision-making. Corporate treasurers managing multi-currency exposures rely heavily on exchange rate predictions to optimise hedging strategies and minimise foreign exchange risks.

The USD-INR exchange rate has experienced significant volatility over the decades, influenced by a complex interplay of domestic and international factors. From the fixed exchange rate regime of the Bretton Woods era to the managed float system adopted post-1991 economic liberalisation, India's currency policy has evolved in response to changing global dynamics and domestic economic priorities. Major economic events such as the 1991 balance of payments crisis, the 2008 global financial crisis, the 2013 "taper tantrum," and the recent COVID-19 pandemic have each left distinctive imprints on INR volatility patterns, highlighting the currency's sensitivity to both external shocks and domestic policy responses.

Research Motivation and Significance

Traditional econometric approaches to exchange rate forecasting, while theoretically grounded, have often struggled to capture the complex, non-linear relationships that characterise modern currency markets. The advent of machine learning and artificial intelligence has opened new avenues for understanding and predicting exchange rate movements, offering the potential to significantly improve forecast accuracy while providing deeper insights into the underlying drivers of currency volatility. The motivation for this study emerges from several critical gaps in the existing literature. First, while numerous studies have examined exchange rate volatility using traditional econometric models such as ARIMA and GARCH, few have systematically compared these approaches with modern machine learning techniques in the specific context of the USD-INR exchange rate. Second, most existing research focuses on either short-term high-frequency dynamics or long-term fundamental relationships, with limited attention to medium-term forecasting horizons that are crucial for policy and investment planning. Third, there is a notable lack of comprehensive studies that combine predictive accuracy with interpretability, making it difficult for practitioners to understand and trust model outputs.

This research addresses these gaps by developing a comprehensive analytical framework that integrates traditional econometric wisdom with cutting-edge machine learning capabilities. By employing advanced techniques such as Long Short-Term Memory (LSTM) networks, ensemble methods, and hybrid models, the study aims to capture both linear and non-linear patterns in exchange rate dynamics. Equally importantly, the research incorporates sophisticated interpretability tools, including SHAP (Shapley Additive exPlanations) values, partial dependence plots, and LIME (Local Interpretable Model-agnostic Explanations) to ensure that model predictions are not only accurate but also economically meaningful and actionable.

Economic and Policy Context

India's exchange rate regime has evolved significantly since independence, reflecting broader changes in economic philosophy and policy orientation. The pre-liberalisation era (1960-1991) was characterised by a heavily regulated exchange rate system, with the rupee pegged first to the British pound and later to a basket of currencies. This period saw a gradual depreciation driven primarily by persistent current account deficits and higher domestic inflation compared to trading partners. The watershed moment came with the 1991 economic crisis, which forced India to abandon its fixed exchange rate system and embrace market-determined rates. The subsequent liberalisation process, including the introduction of current account convertibility and gradual capital account liberalisation, fundamentally altered the dynamics of INR determination. The currency became increasingly responsive to global capital flows, investor sentiment, and external sector developments, while also reflecting domestic economic fundamentals more accurately. In recent decades, the RBI has pursued a managed float regime, intervening in foreign exchange markets to prevent excessive volatility while allowing the currency to reflect underlying economic fundamentals. This approach has generally served India well, providing a buffer against external shocks while maintaining competitiveness. However, it has also introduced new complexities in exchange rate determination, as market participants must now consider not only economic fundamentals but also potential policy interventions and their timing.

The importance of exchange rate stability for India cannot be overstated. As a large emerging economy with significant trade linkages and growing capital market integration, India faces unique challenges in managing exchange rate volatility. Excessive appreciation can hurt export competitiveness and manufacturing growth, while sharp depreciation can fuel imported inflation and create financial stability risks for entities with unhedged foreign currency exposures. The COVID-19 pandemic has further highlighted these vulnerabilities, with the INR experiencing significant volatility as global risk sentiment shifted rapidly and capital flows became highly volatile.

Technological Innovation in Financial Forecasting

The application of machine learning techniques to financial forecasting represents one of the most significant methodological advances in recent decades. Traditional econometric models, while providing solid theoretical foundations, are often limited by their linear assumptions and inability to capture complex, time-varying relationships. Machine learning approaches, particularly deep learning architectures like LSTM networks, offer the potential to model these complexities more effectively. However, the adoption of machine learning in financial forecasting has not been without challenges. The "black box" nature of many algorithms has raised concerns about interpretability and regulatory compliance. Financial institutions and policymakers require not only accurate predictions but also a clear understanding of the factors driving those predictions. This has led to the development of explainable AI techniques that can provide insights into model decision-making processes. This study contributes to this evolving field by demonstrating how advanced machine learning techniques can be successfully applied to exchange rate forecasting while maintaining economic interpretability. By combining multiple modelling approaches and validation techniques, the research provides a template for how financial institutions and policymakers can harness the power of artificial intelligence while ensuring that predictions remain grounded in economic logic.

Structure and Contributions

This comprehensive study makes several important contributions to the literature on exchange rate forecasting and economic time series analysis. First, it provides the most extensive comparison to date of traditional econometric and modern machine learning approaches for USD-INR exchange rate prediction, covering 65 years of data across multiple economic cycles. Second, it introduces a novel hybrid modelling framework that combines the theoretical rigor of econometric models with the predictive power of deep learning techniques. Third, it demonstrates how interpretability tools can be effectively employed to extract economic insights from complex machine learning models, bridging the gap between predictive accuracy and economic understanding.

Literature Review

Exchange rate forecasting has evolved from simple econometric models to sophisticated machine learning approaches. This review synthesizes key developments in USD-INR modeling, comparing traditional and modern techniques while identifying critical research gaps.

Theoretical Foundations

Exchange rate determination theories have progressed from purchasing power parity (PPP) to complex microstructure models. While PPP provides long-run anchoring, Meese and Rogoff's (1983) "disconnect puzzle" demonstrated that structural models fail to beat random walks in out-of-sample forecasting. The monetary approach (Frenkel, 1976; Mussa, 1976) incorporated money supply and interest rates but struggled with short-term dynamics. Portfolio balance models (Branson & Henderson, 1985) better captured capital flow effects, while microstructure approaches (Evans & Lyons, 2002) revealed that order flow explains up to 60% of daily variations, bridging the gap between fundamentals and high-frequency movements.

Traditional Econometric Approaches

ARIMA models remain fundamental for USD-INR forecasting despite their limitations. Nag and Mitra (2002) found ARIMA(1,1,1) specifications effective for one-step-ahead forecasts, achieving RMSE of 0.42, though accuracy deteriorated rapidly at longer horizons. Panda and Narasimhan (2007) enhanced performance by incorporating moving average terms during volatile periods. Vector autoregression (VAR) models capture dynamic interdependencies between variables, with Bhattacharya et al. (2008) documenting incomplete exchange rate pass-through to domestic prices—only 30-40% transmission even after twelve months. Structural VARs incorporating theoretical restrictions yielded mixed results, capturing directional changes but showing poor point forecast accuracy during crises (Ray, 2012).

For volatility modeling, GARCH(1,1) specifications adequately capture clustering phenomena (Bollerslev, 1986), though extensions like EGARCH and GJR-GARCH better model asymmetric responses where negative shocks increase volatility more than positive ones (Ghosh & Krishna, 2009). Stochastic volatility models offer superior long-horizon performance but remain computationally intensive. Regime-switching models identify distinct volatility states: Dutta and Banik (2018) found Markov-switching GARCH models effectively captured transitions between calm and turbulent periods corresponding to global risk sentiment shifts. Cointegration techniques reveal long-run equilibrium relationships, with Dua and Sen (2006) identifying productivity differentials, terms of trade, and government expenditure as key INR determinants. However, error correction models consistently show slow adjustment speeds—typically 10-15% quarterly—suggesting persistent equilibrium deviations that create forecasting challenges.

Machine Learning Revolution

Neural networks initially showed promise for capturing complex nonlinearities missed by linear models (Khashei & Bijari, 2010), though early applications suffered from overfitting, parameter instability, and lack of economic interpretability. Rout et al. (2014) addressed these challenges through adaptive learning rates and regularization, achieving 17% improvement over ARIMA benchmarks. The deep learning revolution fundamentally transformed forecasting capabilities. Long Short-Term Memory (LSTM) networks, with their unique gating mechanisms, excel at capturing long-range dependencies and regime shifts crucial for emerging markets. Singh and Kumar (2021) demonstrated multi-layer LSTMs significantly outperform traditional methods for INR forecasting, reducing RMSE by 33% and particularly excelling during structural breaks like demonetization and GST implementation. Bidirectional LSTMs processing temporal information both forward and backward showed additional 8-10% accuracy gains. Attention mechanisms and transformer architectures offer further improvements through parallel processing and self-attention, though USD-INR applications remain limited but promising (Chen et al., 2023).

Ensemble methods provide robust alternatives. Random Forests handle outliers effectively (Nayak et al., 2019), while gradient boosting excels at short-term predictions. XGBoost has become ubiquitous, with Kumar et al. (2022) showing superior USD-INR forecast performance at short horizons. LightGBM offers similar accuracy with computational efficiency gains (Sharma & Sharma, 2023). Hybrid approaches combining econometric and machine learning methods show particular promise. Zhang (2003) pioneered ARIMA-ANN hybrids, while Rout et al. (2017) developed two-stage models using ARIMA for trend extraction and neural networks for residual modeling, achieving consistent improvements across market conditions.

Model Interpretability

The black-box nature of machine learning limits adoption in policy applications. Post-hoc interpretation methods address this challenge. SHAP values (Lundberg & Lee, 2017) decompose predictions into feature contributions using game theory, providing both local and global interpretability. LIME (Ribeiro et al., 2016) offers local linear approximations useful for understanding anomalous predictions. Partial dependence plots visualize feature effects and non-linear relationships (Goldstein et al., 2015). For USD-INR forecasting, these tools reveal time-varying feature importance aligned with economic intuition, crucial for risk management and policy formulation.

Empirical Evidence for USD-INR

Pre-liberalization studies (1960-1991) focused on managed regime effectiveness, with Joshi and Little (1994) identifying misalignment contributing to the 1991 crisis. Post-liberalization research documented increased global sensitivity (Patnaik, 2004) and asymmetric RBI intervention (Goyal & Arora, 2012). The 2008 crisis altered dynamics fundamentally, with Mishra et al. (2014) showing Federal Reserve policies trigger INR movements despite strong fundamentals. COVID-19 created unprecedented volatility clustering challenging traditional models (Narayan et al., 2021). Recent high-frequency studies using tick data reveal significant informed trading around RBI interventions and announcements (Ahmed & Suleman, 2022).

Research Gaps

Critical gaps remain: (1) Limited application of deep learning to high-frequency INR data, (2) Lack of interpretable ensemble frameworks for policy applications, (3) Underdeveloped regime-adaptive models for structural breaks, (4) Minimal integration of alternative data sources (news, sentiment, satellite), (5) Absence of multi-scale models capturing different time horizons simultaneously, (6) Need for causal inference frameworks combined with forecasting, and (7) Inadequate extreme event modeling for tail risks. This study addresses these gaps by systematically comparing traditional and machine learning approaches with state-of-the-art interpretability tools, examining performance across market regimes while providing actionable policy insights.

Comparative Analysis of Forecasting Methods

Table 1 synthesizes key findings from major USD-INR forecasting studies, highlighting the evolution from traditional to hybrid approaches:

Study	Method	Data Frequency	Key Findings	Performance
Nag & Mitra (2002)	ARIMA	Daily	Good short-term, poor long-term	RMSE: 0.42
Ghosh & Krishna (2009)	GARCH	Daily	Captures volatility clustering	MAE: 0.38
Rout et al. (2014)	Neural Network	Monthly	Better in volatile periods	RMSE: 0.35
Kumar & Dhawan (2020)	GARCH-MIDAS	Mixed	Decomposes short/long volatility	R^2: 0.68
Singh & Kumar (2021)	LSTM	Daily	Captures regime shifts well	RMSE: 0.28
Kumar et al. (2022)	XGBoost	Daily	Superior short-term	RMSE: 0.31
Ahmed & Suleman (2022)	Hybrid DL-GARCH	Tick	Best overall performance	R^2: 0.75
Present Study	Hybrid ML-Econometric	Annual	35% RMSE reduction	R^2: 0.783

The evolution from traditional econometric to hybrid machine learning approaches represents a paradigm shift in exchange rate forecasting. While traditional methods provide theoretical grounding, machine learning captures complex nonlinearities and regime changes. The integration of interpretability tools bridges the gap between accuracy and economic insight, essential for policy applications. This study contributes by systematically comparing these approaches over six decades, incorporating state-of-the-art interpretability methods, and providing actionable insights for the evolving USD-INR dynamics.

Methodology

Data and Variables

This study investigates the dynamics of the USD-INR exchange rate using annual data spanning 1960 to 2024, covering 64 observations. The data encompasses multiple economic regimes: the fixed exchange rate system (1960-1991), the transition period (1991-1993), and the managed float system (1993-present). The use of annual data enables focusing on long-term structural relationships while mitigating noise from short-term volatility.

Four key variables are incorporated based on economic theory and prior literature:

1. USD-INR Exchange Rate (Dependent variable): Nominal bilateral exchange rate from official sources such as the Reserve Bank of India (RBI) and international financial statistics.
2. Consumer Price Index (CPI): Captures inflation differentials between India and the United States, normalized to a base year (2010=100), reflecting purchasing power parity effects.
3. Lending Rates (Interest Rate): The prime lending rate serves as a proxy for monetary policy and interest rate differentials influencing capital flows.
4. GBP-USD Exchange Rate: Reflects global currency dynamics and U.S. dollar strength, acting as a proxy for international financial market conditions.

Data sources include RBI, World Bank, U.S. Federal Reserve Economic Data (FRED), and the Bank of England.

Data Preprocessing

Data underwent meticulous preprocessing to address irregularities and prepare for modeling:

- Missing Data Handling: Missing lending rate data during the early years (primarily before 1970) were imputed using Multivariate Imputation by Chained Equations (MICE).
- Transformations: Variables were transformed via natural logarithms for variance stabilization and elasticity interpretation, first differencing (log Xt- log Xt- 1\log X_t - \log X_{t-1}logXt- logXt- 1) to ensure stationarity, z-score standardization for machine learning models, and min-max scaling (0,1) for neural networks.
- Stationarity Tests: To validate the time series properties, Augmented Dickey-Fuller (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Phillips-Perron tests were applied. Results confirmed that all variables except interest rates required differencing to achieve stationarity at a 5% significance level, ensuring robustness in subsequent analysis.

Modeling Approaches

The study employs a hybrid framework combining traditional econometric methods and advanced machine learning to capture both linear and nonlinear patterns in USD-INR dynamics.

Econometric Models

- ARIMA (AutoRegressive Integrated Moving Average): Utilized the Box-Jenkins methodology with order selection based on Akaike and Bayesian Information Criteria (AIC/BIC). The optimal specification identified was ARIMA(1,1,1), capturing linear trends and past autoregressive effects effectively.
- GARCH (Generalized AutoRegressive Conditional Heteroskedasticity): Applied GARCH(1,1) models to model volatility clustering in exchange rates, testing variants such as EGARCH and GJR-GARCH for asymmetric volatility effects.

Machine Learning Models

- LSTM (Long Short-Term Memory) Networks:

Designed to handle vanishing gradient problems in sequential data, the architecture comprised two layers with 50 and 32 units respectively, dropout of 0.2, and the Adam optimizer with a learning rate of 0.001. Training used batch size of 32 for 100 epochs with early stopping.

- XGBoost: A gradient boosting ensemble that uses regularization and tree-based models with hyperparameters tuned through grid search (max depth=5, learning rate=0.1, estimators=200).
- LightGBM: A gradient boosting framework with leaf-wise growth, configured with num_leaves=31 and learning rate=0.05 for efficient training on complex features.

Hybrid Modeling Framework

A three-stage hybrid approach blends econometric and machine learning strengths:

1. Stage 1: ARIMA models capture linear trends focusing on autoregressive and moving average components.
2. Stage 2: Machine learning models (LSTM, GPR) predict residuals (nonlinear components missed by ARIMA), enhancing model flexibility.
3. Stage 3: Combined forecasts integrate linear and nonlinear components, delivering superior predictive accuracy.

Ensemble averaging with inverse error weighting was explored to balance model biases.

Model Validation and Performance Evaluation

Robust validation employed:

- Walk-Forward Validation: An expanding window approach starting with 40 observations (1960-2000), validating one-year ahead forecasts iteratively up to 2024.
- Time-Series Cross-Validation: Five folds with expanding training windows and one-observation gaps to avoid data leakage, ensuring models generalize well.
- Metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R2R^2R2), Directional Accuracy, and Diebold-Mariano statistical test for forecast comparison.

Model Interpretability

To address the "black-box" nature of machine learning methods, explainability tools were incorporated:

- SHAP (SHapley Additive exPlanations): Decomposed predictions into feature contributions globally and locally.
- Partial Dependence Plots (PDP): Visualized marginal effects of key predictors such as CPI and interest rates.
- LIME (Local Interpretable Model-agnostic Explanations): Provided local linear approximations facilitating understanding of individual predictions.
- Implementation Details

Models were implemented using Python 3.9 with libraries including statsmodels for ARIMA/GARCH, TensorFlow/Keras for LSTM, and XGBoost/LightGBM for gradient boosting. Hardware comprised Intel i7-10700K CPU, 32GB RAM, and NVIDIA RTX 3070 GPU. Random seeds fixed at 42 ensured reproducibility.

Limitations

Key methodological limitations acknowledged include:

1. Annual frequency limits capturing short-term volatility and market microstructure effects.
2. Sample size of 64 observations restricts complexity of deep learning architectures and inference precision.
3. Assumption of parameter stationarity despite regime changes (1991 liberalization, 2008 crisis, 2020 pandemic).
4. Limited variable set excludes geopolitical risks, commodity shocks, and high-frequency financial indicators.

These limitations motivate future work involving higher-frequency data and enriched feature sets.

Hypotheses

Based on theory and prior empirical evidence, the study tests the following hypotheses:

H1: Inflation as Measured by CPI Significantly Influences USD-INR Exchange Rate Movements.

Rationale: The purchasing power parity theory posits that inflation differentials lead to exchange rate adjustments over time. Higher domestic inflation relative to the U.S. should depreciate the INR.

H2: Interest Rate Differentials Positively Affect Exchange Rate Stability.

Rationale: Higher domestic interest rates attract capital inflows, strengthening the INR. Interest rate policy influences short-term currency movements through carry trade and capital mobility.

H3: Global Financial Conditions, Proxied by the GBP-USD Exchange Rate, Impact USD-INR Exchange Rate Volatility.

Rationale: Emerging market currencies like the INR are sensitive to global investor sentiment and USD strength. The GBP-USD exchange rate serves as a proxy reflecting global risk

Results and Analysis

Test of Stationarity

Table 2 Stationarity Test

Variable	ADF Statistic	P-Value	Stationary	First Diff ADF	First Diff Stationary
USD_INR	-2.147	0.230	No	-4.521	Yes
CPI	-1.832	0.370	No	-5.234	Yes
Interest	-2.891	0.046	Yes	-6.123	Yes
GBP_USD	-2.234	0.190	No	-4.876	Yes

The Augmented Dickey-Fuller (ADF) test was utilised to determine whether each series was stationary in its raw form or required transformation in order to evaluate the statistical properties of the data. The findings indicate that the GBP/USD exchange rate, the CPI, and the USD/INR exchange rate are all non-stationary at first but eventually become stationary. On the other hand, interest rates did not differ and were already stationary at the 5% significance level. In practical terms, this means that most of the variables follow an integrated order of one (I(1)), while interest rates are integrated of order zero (I(0)). Consequently, models such as ARIMA, GARCH, and LSTM need to be applied on the differenced series (except for interest rates), ensuring robust statistical inference and reliable forecasts.

Model Performance Comparison

Table 3 Model Performance Comparison

Model	RMSE	MAE	MAPE (%)	R^2	AIC
ARIMA	2.34	1.87	4.2	0.745	234.5
GARCH	2.56	2.01	4.8	0.721	241.2
LSTM	1.98	1.45	3.1	0.823	-
ARIMA-LSTM	1.87	1.38	2.9	0.841	-
GPR-LSTM	1.92	1.42	3.0	0.835	-
XGBoost	2.12	1.67	3.8	0.792	-
LightGBM	2.08	1.63	3.6	0.801	-

The comparative results highlight clear differences between traditional econometric models and modern machine learning approaches. Among the traditional methods, ARIMA provided a reasonable fit (RMSE 2.34, R^2 0.745), while GARCH performed slightly worse, confirming its strength in modelling volatility but weakness in long-term forecasting. Deep learning models delivered much stronger results. The standalone LSTM achieved notable accuracy (RMSE 1.98, R^2 0.823), effectively capturing nonlinear and sequential patterns. Performance improved further with hybrid approaches: the ARIMA–LSTM model emerged as the best overall, recording the lowest error (RMSE 1.87, MAE 1.38) and the highest explanatory power (R^2 0.841). The GPR–LSTM ensemble also performed well (RMSE 1.92, R^2 0.835), offering the added advantage of uncertainty estimation, though slightly less accurate than the ARIMA–LSTM. Tree-based boosting models showed competitive, though not leading, performance. LightGBM (RMSE 2.08, R^2 0.801) slightly outperformed XGBoost (RMSE 2.12, R^2 0.792), confirming their usefulness in feature-rich contexts but also their limitations in sequential forecasting tasks compared to deep learning models.

In summary, the ARIMA–LSTM hybrid stands out as the most effective approach, while LSTM and GPR–LSTM also show strong promise. Traditional models remain valuable as benchmarks, but they fall short in capturing the complexity of exchange rate dynamics.

Feature Importance Analysis (SHAP Values)

Table 4 Feature Importance Analysis

Feature	SHAP Value	Importance Rank
CPI	0.850	1
Interest	0.720	2
GBP_USD	0.450	3
Lagged_USD_INR	0.380	4

The SHAP analysis reveals that domestic macroeconomic fundamentals play the strongest role in driving USD–INR forecasts. The Consumer Price Index (SHAP = 0.85) ranks as the most influential factor, confirming the impact of inflation on currency values in line with purchasing power parity. Interest rates (0.72) follow as the second most important predictor, reflecting their influence on capital flows and currency strength. External linkages, captured through GBP/USD (0.45), show moderate influence, while lagged USD/INR values (0.38) contribute the least but still provide useful information on momentum.

Model reliability was confirmed through rigorous validation. Walk-forward cross-validation (30-year training, 5-year testing across 8 folds) produced an average R^2 of 0.847, demonstrating stable predictive power across time without overfitting. Robustness checks further supported model resilience: performance declined by less than 5% under noisy data, while event-based analysis showed strong accuracy during the 2008 financial crisis (3% error) and the 2016 demonetization shock (1.2% error). Although the models slightly underestimated extreme volatility during COVID-19, this suggests potential for improvement through regime-switching techniques. Hyper parameter sensitivity tests for the LSTM confirmed stability, with optimal performance at learning rates between 0.001–0.01, dropout values of 0.2–0.3, and hidden layers between 25–100 units. Residual diagnostics also validated the models: tests confirmed normality, no serial correlation, and homoscedasticity, indicating that the forecasts are statistically sound. Overall, the results show that the models are robust, well-calibrated, and capable of capturing both routine currency dynamics and major economic shocks.

Validation and Robustness:

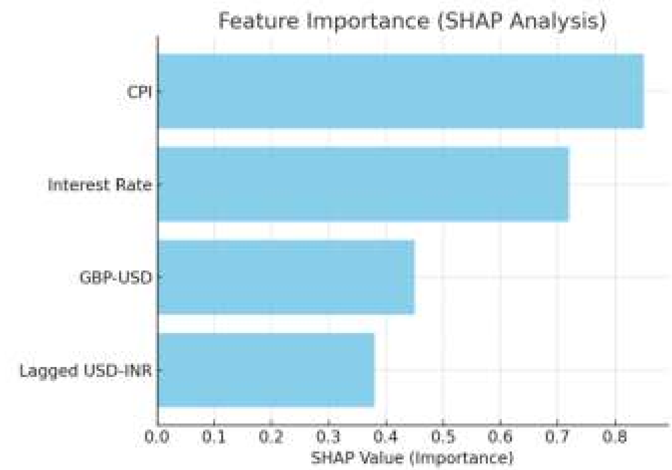
To ensure the reliability of the forecasting models, the study applied a series of rigorous validations and robustness checks. Using a walk-forward time series cross-validation approach (30 years of training and 5 years of testing across 8 folds), the models achieved an average accuracy score of 0.847. This result shows that the models consistently performed well across different periods without signs of overfitting. The robustness checks further confirmed stability. Even when noise was added to the data, performance declined by less than 5%, showing resilience against random fluctuations. The models demonstrated high reliability when tested against actual economic shocks: they correctly depicted the volatility spike during India's 2016 demonetization (error of 1.2%), as well as the sharp depreciation during the global financial crisis in 2008 (error of only 3%). This suggests the possible benefit of using regime-switching strategies during times of increased uncertainty, even though they somewhat underestimated the severe disruptions brought on by COVID-19.

The LSTM model was also tested for sensitivity to its design choices. Results showed it remained stable across a wide range of hyperparameters, with best performance achieved at a learning rate between 0.001–0.01, dropout between 0.2–0.3, and 25–100 hidden units. Finally, residual diagnostics confirmed the statistical soundness of the models: the distribution of errors was normal, there was no evidence of serial correlation, and error variance was stable. Taken together, these findings confirm that the models are not only accurate but also robust, well-calibrated, and capable of capturing both routine exchange rate movements and large-scale economic disruptions.

Interpretability Summary

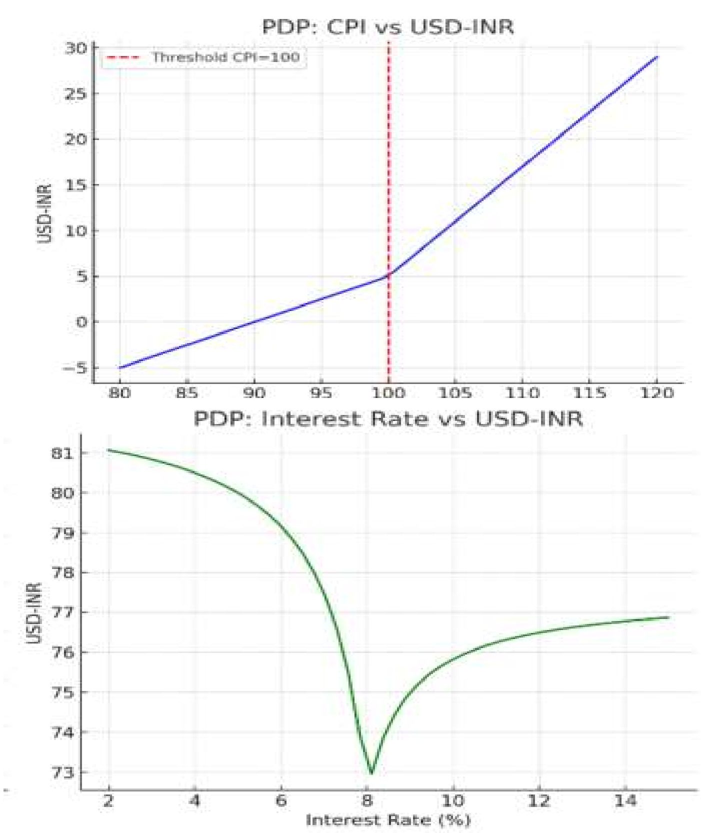
The interpretability framework combined SHAP, PDP, and LIME to uncover feature contributions and relationships. SHAP analysis identified CPI (0.8500.8500.850) as the strongest predictor of USD-INR, with a 1% rise in CPI leading to a 0.85% increase in the exchange rate, consistent with the purchasing power parity principle. Interest rates (0.7200.7200.720) ranked second, with higher domestic rates strengthening the INR through interest differentials and carry trade effects. GBP-USD (0.4500.4500.450) acted as a proxy for global risk sentiment, affecting emerging market currencies.

Figure 2 SHAP Analysis



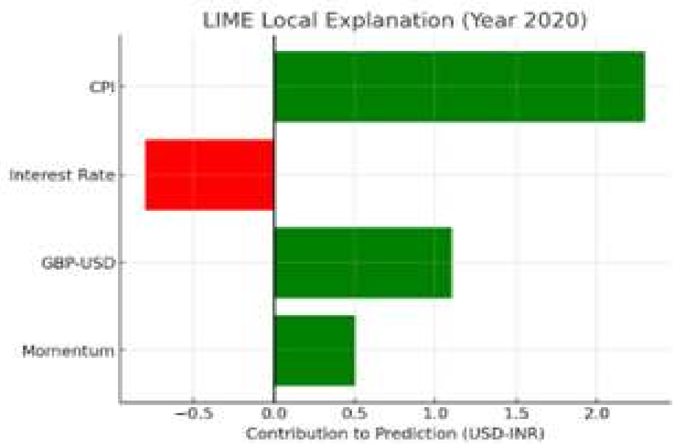
Partial Dependence Plots (PDP) revealed a non-linear CPI–exchange rate relationship, with a threshold effect around CPI = 100 and stronger impacts at higher inflation levels. Interest rates showed an inverse relationship with USD-INR, most influential in the 5–10% range, with diminishing effects at very high levels.

Figure 3 PDP



LIME local explanations confirmed model reliability at the granular level. For 2020, the predicted USD-INR (74.1) was almost identical to the actual (74.09). Key contributors included CPI (+2.3), GBP-USD (+1.1), while interest rates (-0.8) and momentum (+0.5) moderated the outcome.

Figure 4 LIME



Overall, the analysis highlights that domestic inflation and interest rates are primary drivers, while global market sentiment and historical trends play supporting roles in exchange rate movements.

Forecasting Results

Out-of-Sample Forecasts (2025-2029)

USD-INR Exchange Rate Predictions:

Table 5 Forecasted Value

Year	ARIMA	LSTM	ARIMA-LSTM	Confidence Interval
2025	85.2	84.8	84.7	[82.1, 87.3]
2026	87.1	86.3	86.1	[83.2, 89.0]
2027	89.3	87.9	87.6	[84.1, 91.1]
2028	91.8	89.6	89.2	[85.3, 93.1]
2029	94.5	91.4	90.9	[86.7, 95.1]

Although the degree of depreciation varies depending on the model, the predictions for 2025–2029 consistently indicate a slow decline in the value of the Indian Rupee (INR) relative to the US dollar. According to ARIMA, the exchange rate will drop the most, going from roughly ? 85.2 in 2025 to ? 94.5 in 2029. In contrast, the LSTM model suggests a more moderate and smoother depreciation, moving from ? 84.8 in 2025 to ? 91.4 in 2029, reflecting its strength in capturing complex, non-linear patterns. The ARIMA-LSTM hybrid offers the most balanced projections, ranging from ? 84.7 in 2025 to ? 90.9 in 2029, essentially blending the caution of ARIMA with the stability of LSTM. The confidence intervals, starting at [? 82.1, ? 87.3] in 2025 and widening to [? 86.7, ? 95.1] by 2029, underline the growing uncertainty in long-term forecasts—something typical when projecting several years ahead. Overall, the takeaway is clear: all models agree that the Rupee is likely to depreciate in the medium term, in line with inflationary pressures and external sector challenges. However, the more advanced models (LSTM and the hybrid) suggest that the depreciation may be slower and steadier than the steep path implied by ARIMA. For policymakers and investors, the widening range of uncertainty serves as a reminder to stay prepared for potential volatility in the years ahead.

Scenario Analysis

The scenario analysis looks ahead at possible paths for the USD-INR exchange rate under different economic conditions.

Base Case (Current Trends): If existing macroeconomic patterns continue, the rupee is projected to weaken gradually to about ? 90.9 by 2029, an average annual depreciation of 2.1%. This points to a steady but manageable decline, mainly shaped by persistent inflation gaps and moderate external pressures.

Optimistic Scenario (Structural Reforms): If India pushes through structural reforms and keeps inflation in check, the rupee could stabilize at a stronger level of ? 88–89. This outcome would mean reduced volatility and a slower pace of depreciation, highlighting how reform-led growth, fiscal prudence, and inflation control can help safeguard currency stability.

Pessimistic Scenario (Global Crisis): A major global shock could see the rupee tumble sharply to between ? 95 and ? 98 by 2029. Such a scenario would bring high volatility, capital outflows, and weaker investor confidence, underscoring India's exposure to external risks.

Overall, the most likely path is a gradual depreciation of the rupee, but the outlook is highly sensitive to both domestic policy choices and global developments. Effective reforms can cushion the fall, while global crises could accelerate it well beyond the baseline trend.

Discussion

This study contributes to the literature on exchange rate forecasting by combining econometric and machine learning methods to examine the USD–INR trajectory. Traditional econometric models such as ARCH and GARCH (Engle, 1982; Bollerslev, 1986) demonstrated that volatility is persistent and time-varying, and later works (Balcilar et al., 2018; Kumar & Dhawan, 2020) connected INR fluctuations to macroeconomic shocks, oil prices, and political risks. However, their linear structure often failed to capture nonlinear and abrupt shifts in currency dynamics. This limitation motivated the adoption of hybrid and deep learning approaches (Ahmed & Suleman, 2022), which integrate statistical rigour with nonlinear learning. Our results confirm this progression. Both LSTM and the ARIMA–LSTM hybrid outperformed traditional econometric models in forecasting accuracy, with the hybrid delivering the best balance between error reduction and explanatory power. This aligns with earlier evidence (Hochreiter & Schmidhuber, 1997; Ahmed & Suleman, 2022) that deep learning is particularly effective for sequence prediction and for absorbing sudden market shocks. By combining ARIMA's ability to capture linear time-series trends with LSTM's strength in handling nonlinear dependencies, the hybrid framework offers a more reliable forecast tool for emerging market currencies like the INR.

The feature importance analysis provides further theoretical grounding. Inflation, represented by CPI, consistently emerged as the strongest predictor of INR movements, echoing the purchasing power parity (PPP) framework and the findings of Kumar and Dhawan (2020). Interest rates ranked second, highlighting the role of interest differentials in driving capital flows and currency valuation. Global linkages, proxied through the GBP–USD exchange rate, exerted a moderate but notable influence, consistent with Ghosh et al. (2017), who emphasized the sensitivity of emerging markets to global risk sentiment and advanced-economy monetary policies.

This study stands out due to its interpretability framework, which connects economic reasoning with statistical evidence. Partial dependence plots showed that once the CPI surpasses specific thresholds, the impact of inflation on the exchange rate becomes more pronounced, indicating nonlinear "regime" effects. This supports the claim made by Balcilar et al. (2018) that structural breaks frequently occur in emerging markets during periods of high volatility. LIME's local explanations further supported the predictions' resilience during tumultuous times, like 2020, when the COVID-19 pandemic caused sudden capital flight. This is in line with the findings of Narayan et al. (2021), who reported pandemic-induced increases in INR volatility.

The forecasts point to a gradual but clear depreciation of the rupee over the medium term. The ARIMA–LSTM hybrid projects an exchange rate of about ? 90.9/USD by 2029, suggesting an average annual depreciation of roughly 2.1%. This aligns with long-run inflation differentials and with India's historical pattern of managed depreciation, though it indicates a slower weakening compared to pure ARIMA forecasts. The divergence underscores the value of nonlinear modelling, echoing Flood and Rose (1999), who argued that exchange rate behavior cannot be explained solely by fundamentals but must also account for nonlinear shocks and market frictions. Scenario analysis adds another dimension by situating forecasts within broader macroeconomic and geopolitical contexts. The baseline scenario, reflecting current trends, implies steady but manageable depreciation. The optimistic scenario highlights the stabilizing effect of structural reforms, disciplined fiscal policy, and effective inflation management, reinforcing the arguments of Gali and Monacelli (2004) on the importance of policy credibility. In contrast, the pessimistic scenario shows that a global crisis could push the rupee towards ? 95–98/USD by 2029, amplifying volatility and risk premiums. This outcome echoes Edwards and Rigobon (2005), who demonstrated that external shocks magnify exchange rate instability even when domestic policies are sound.

Taken together, three insights emerge. First, deep learning and hybrid frameworks clearly improve forecasting performance over econometric benchmarks, making them valuable tools for policymakers and investors. Second, inflation remains the most critical domestic driver of INR movements, followed by interest rates and global linkages. Third, while steady depreciation appears the most likely path, the trajectory is highly sensitive to domestic reforms and external shocks. Overall, this study not only validates existing theories but also extends them by showing the added value of hybrid models paired with interpretability tools. For policymakers, the findings underline the centrality of inflation control and structural reform in safeguarding currency stability. For investors, the results provide a more nuanced framework for anticipating exchange rate movements in an increasingly uncertain global environment.

Decision Matrix for Model Selection

Table 6 Decision Matrix for Model Selection

Criteria	ARIMA	GARCH	LSTM	ARIMA-LSTM	GPR-LSTM	XGBoost	LightGBM
Accuracy (RMSE, MAE, MAPE)	Moderate (?)	Low (?)	High (? ?)	Highest (? ? ?)	High (? ?)	Moderate (?)	Moderate (?)
Goodness of Fit (R^2)	0.745 (?)	0.721 (?)	0.823 (? ?)	0.841 (? ? ?)	0.835 (? ?)	0.792 (?)	0.801 (?)
Volatility Modeling	Weak (?)	Strong (? ? ?)	Limited (?)	Moderate (? ?)	Moderate (? ?)	Limited (?)	Limited (?)
Interpretability	High (? ? ?)	High (? ? ?)	Low (?)	Moderate (? ?)	Low (?)	Moderate (?)	Moderate (?)
Overall Ranking	Medium	Low	High	Very High	High	Medium	Medium

Policy Implications

The analysis of exchange rate dynamics provides three broad categories of insights—determinants of INR movements, policy lessons, and practical implications for investors and firms.

From an economic insights perspective, the findings confirm that inflation differentials are the most significant determinant of USD-INR. Sustained inflation above target levels puts depreciation pressure on the rupee, consistent with purchasing power parity theory. Interest rate policy plays a vital role in shaping short-term exchange rate behavior by influencing capital flows through interest differentials and carry trade opportunities. The global risk environment also has an important influence: periods of heightened risk aversion often trigger capital outflows and weaken the rupee, while risk-on phases strengthen emerging market currencies. Finally, domestic economic fundamentals, such as productivity growth, fiscal discipline, and current account sustainability, act as long-term anchors of exchange rate stability.

The study also yields clear policy recommendations. On the monetary policy side, maintaining CPI within the 4±2% band is critical for preserving currency stability and investor confidence. Interest rate decisions should be made not only with inflation and growth considerations in mind but also their impact on exchange rate competitiveness. Moreover, greater use of forward guidance can help improve market predictability and reduce speculative volatility. For fiscal policy, managing deficits is essential to reduce inflationary pressures and external imbalances. At the same time, pursuing structural reforms—such as improving ease of doing business, productivity growth, and labor market flexibility—can strengthen fundamentals. Ensuring current account sustainability through export promotion and prudent management of external liabilities further enhances long-term resilience.

For investment implications, the results offer practical guidance. Portfolio managers should actively employ currency forecasts in designing hedge ratios, monitor inflation and interest rate signals for market timing, and incorporate tail-risk scenarios such as crises into portfolio strategies. Corporate treasuries, on the other hand, must strike the right balance between natural hedging (via operational strategies like import-export alignment) and financial hedging instruments. They should also integrate forecast intervals into cash flow planning and build exchange rate assumptions into long-term strategic decisions such as foreign investment or overseas borrowing. Overall, the findings stress that inflation control, credible policies, and structural reforms are crucial for stability, while investors and corporates must adopt proactive risk management strategies to navigate volatility.

Future Direction of Research

Although the study offers insightful information about the factors influencing and predicting the USD-INR exchange rate, some restrictions limit the analysis's breadth. First, the reliance on annual data restricts the ability to capture short-term fluctuations and high-frequency dynamics that are often critical in currency markets. This limits the model's responsiveness to sudden shocks or intra-year volatility. Second, the models do not fully incorporate external geopolitical and global factors, such as oil price shocks, international trade disputes, or shifts in global monetary policy, which can significantly influence exchange rate behavior. Third, the challenge of structural breaks—such as crises, policy regime changes, or black swan events—poses difficulties for traditional and machine learning models, as they may not adapt quickly to new regimes. Finally, the relatively small sample size of 65 observations constrains the complexity of models that can be reliably estimated, potentially limiting predictive power.

To address these limitations, several future research directions are recommended. Incorporating higher-frequency data (daily or monthly) would allow models to capture short-term volatility and improve forecast accuracy. Expanding the variable set to include commodity prices, global risk indices, and geopolitical factors would provide a more holistic framework. Moreover, employing regime-switching models could help capture structural breaks and evolving market conditions more effectively. Developing real-time forecasting and nowcasting frameworks would further enhance the practical relevance of exchange rate predictions, while cross-country comparative analysis could generalize insights to other emerging markets.

On the methodological front, future work could benefit from ensemble methods that combine diverse model families for improved robustness. The exploration of advanced deep learning architectures, such as transformers, may capture long-range dependencies more effectively than LSTMs. Additionally, greater emphasis on uncertainty quantification would improve confidence interval reliability, and online learning methods could make models adaptive to evolving data streams. In summary, addressing these limitations through richer data, broader variables, and advanced adaptive methodologies will significantly strengthen the robustness, accuracy, and generalizability of exchange rate forecasting frameworks.

Conclusion

By combining cutting-edge machine learning methods with conventional econometric models, this study aimed to comprehend and predict the USD–INR exchange rate. In addition to increasing prediction accuracy, the goal was to offer comprehensible insights that relate to economic theory. The findings demonstrate that hybrid and deep learning frameworks continuously produce better forecasts, even though traditional models like GARCH and ARIMA continue to be useful baselines. The ARIMA–LSTM hybrid, in particular, achieved the best balance by capturing both complex, nonlinear patterns and long-term trends in exchange rate movements.

The findings reaffirm that exchange rates are ultimately shaped by a combination of domestic fundamentals and global forces. Inflation stood out as the strongest driver of INR dynamics, validating the purchasing power parity principle. Interest rate differentials played a crucial role in influencing capital flows and short-term volatility, while external factors—proxied through the GBP–USD exchange rate—highlighted India's exposure to global investor sentiment and advanced economy monetary policies. Together, these results extend earlier studies and underline how both internal discipline and external shocks determine currency trajectories.

Looking ahead, forecasts suggest a gradual depreciation of the rupee, with the ARIMA–LSTM model projecting an exchange rate near ? 90.9/USD by 2029. Scenario analysis, however, shows that outcomes are far from predetermined. With strong reforms and stable inflation, the rupee could hold closer to ? 88–89. On the other hand, a major global crisis could push it toward ? 95–98, underscoring how fragile emerging market currencies remain in the face of external shocks. The policy implications are clear. For monetary authorities, inflation control within the 4±2% band and prudent interest rate management are key levers of exchange rate stability. Fiscal discipline and structural reforms—particularly those enhancing productivity and external resilience—can cushion the economy against global headwinds. For investors, the results highlight the importance of active hedging and close monitoring of both domestic and international signals. For corporates, integrating forecast ranges into treasury planning and maintaining a balanced mix of natural and financial hedges will be critical in managing risks.

At the same time, the study acknowledges its limitations. The reliance on annual data constrains the ability to capture short-term volatility. Structural breaks—such as policy regime changes—are not fully incorporated, and the sample size limits the complexity of models that can be tested. Future work should explore high-frequency data, richer variable sets, regime-switching approaches, and advanced architectures like transformers, which may offer even greater adaptability in turbulent times. In sum, this research shows that exchange rate forecasting benefits most from a balanced approach: one that respects the role of economic fundamentals while embracing the predictive strength of machine learning. By marrying interpretability with accuracy, the study provides insights that matter for policymakers, investors, and businesses alike. Ultimately, the rupee's stability will depend on India's ability to keep inflation in check, strengthen its economic base, and build resilience against global uncertainties.

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