TELKOMNIKA Telecommunication Computing Electronics and Control
Vol. 24, No. 6, December 2026, pp. 2084~2092
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v24i6.27928

Hybrid ARIMA-LSTM forecasting for Indian rupee exchange rate dynamics

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Article Info

Article history:

Received Mar 12, 2026
Revised Jul 12, 2026
Accepted Aug 28, 2026

Keywords:

Exchange rate forecasting
Financial time series
Hybrid ARIMA-LSTM
Indian rupee
Long short-term memory
Machine learning forecasting
Time series prediction

ABSTRACT

Exchange rate forecasting plays a critical role in international trade, financial planning, and economic policy analysis. This study proposes a hybrid forecasting framework that integrates classical statistical modeling with artificial intelligence techniques to predict the exchange rates of major global currencies against the Indian rupee (INR). Monthly exchange rate data for United States dollar (USD), British pound sterling (GBP), and Japanese yen (JPY) from May 1966 to February 2025, and euro (EUR) from January 1999 to February 2025, were analyzed. Stationarity of the series was evaluated using the augmented Dickey-Fuller (ADF) test and achieved through first-order differencing. An autoregressive integrated moving average (ARIMA) model was first employed to capture linear temporal dependencies in the time series. Residual patterns from the ARIMA forecasts were then modeled using a long short-term memory (LSTM) neural network to learn nonlinear relationships. The final hybrid forecast combines ARIMA predictions with LSTM-based residual corrections. Experimental results indicate that the hybrid ARIMA–LSTM model improves forecasting accuracy compared with standalone statistical models, providing a robust framework for long-term exchange rate prediction.

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1. INTRODUCTION

Exchange rate forecasting is important in international finance because currency fluctuations affect international trade, investment decisions, and economic policy. However, exchange rates are difficult to predict because their behaviour changes over time and may include both linear and nonlinear patterns. Traditional statistical models have been widely used to analyse time-series data and generate forecasts.

The autoregressive integrated moving average (ARIMA) model, described by Box and Jenkins [1], is a widely used method for time-series forecasting. Before applying ARIMA, the stationarity of the data must be examined. The augmented Dickey-Fuller (ADF) test is commonly used for this purpose [2]. Previous studies have applied ARIMA to forecast the Indian rupee (INR) against the United States dollar (USD) [3] and to examine the daily exchange rates of the rupee against major currencies [4]. Other research has compared ARIMA with exponential smoothing and recurrent neural networks for currency forecasting [5]. Comparisons between ARIMA and long short-term memory (LSTM) models have also been reported in time-series forecasting studies [6], [7].

Deep learning methods have received increasing attention because they can learn complex patterns from historical data. Recent studies have investigated adaptive signal decomposition and attention-based LSTM models for exchange rate forecasting [8], [9]. Other research has examined hybrid forecasting

methods, exchange rate volatility during economic crises, and deep learning approaches for currency prediction [10]-[12]. Related studies have also compared statistical and deep learning methods for financial time-series forecasting, including stock market prediction [13]-[15]. Further research has explored LSTM-based exchange rate forecasting using macroeconomic indicators and reviewed recent developments in deep learning for financial prediction [16], [17].

Hybrid forecasting methods combine statistical models with machine learning techniques. In a hybrid ARIMA-LSTM framework, ARIMA models the linear component of a time series, while LSTM learns patterns in the residuals produced by ARIMA. Research has examined this approach for stock market forecasting and other financial time-series applications [18]. Recent studies have also explored different machine learning models for exchange rate prediction [19], the use of text mining with deep learning [20], comparisons of neural network architectures [21], explainable deep learning methods [22], and LSTM-based forecasting for specific currency pairs [23]. Studies using daily and monthly exchange rate data have further examined machine learning methods and combinations of forecasting models [24], [25].

Despite these developments, further research is needed to evaluate hybrid forecasting models across multiple currencies using long-term historical data. This study develops a hybrid ARIMA-LSTM framework to forecast the exchange rates of four major currencies, namely USD, British pound sterling (GBP), and Japanese yen (JPY) and euro (EUR), against the Indian rupee. The study uses monthly exchange rate data covering several decades. First, ARIMA is applied to model the linear patterns in each exchange rate series. An LSTM network is then used to model the remaining residual patterns. Finally, the forecasting performance of the hybrid model is compared with that of the standalone ARIMA model. The study aims to determine whether incorporating LSTM-based residual modelling improves forecasting performance across the selected currencies.

2. THE PROPOSED HYBRID FORECASTING MODEL

Forecasting financial time series requires models capable of capturing both linear statistical structures and nonlinear temporal dependencies. Classical models such as ARIMA capture linear patterns in stationary time series, while deep learning models such as LSTM can learn nonlinear sequential relationships. Therefore, this study proposes a hybrid ARIMA–LSTM framework that integrates statistical modeling with deep learning to improve exchange rate forecasting accuracy.

2.1. ARIMA model

The ARIMA model is one of the most commonly used statistical approaches for analyzing and forecasting univariate time series. It combines autoregressive, differencing, and moving average components to represent temporal relationships after the series has been transformed into a stationary form. The general ARIMA model is expressed as:

$$ARIMA\ (p, d, q)$$

where: p = order of the autoregressive component; d = degree of differencing required for stationarity; and q = order of the moving average component. The mathematical representation of the ARIMA model is given by (1).

$$\phi(B)(1\ -\ B)^d X_t = \theta(B)\varepsilon_t \quad (1)$$

where: X_t = observed time series value at time t; B = backshift operator; d = order of differencing; and ε_t = white noise error term. The autoregressive and moving average components of the model are represented by (2).

$$X_t = c + \sum_{i=1}^{p} \phi_i X_{t-1} + \varepsilon_t \quad (2)$$

The moving average component of order q is expressed as (3).

$$X_t = \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} \quad (3)$$

Together, these components enable ARIMA to model linear temporal relationships in stationary time series.

2.2. LSTM neural network

LSTM is a specialized recurrent neural network architecture designed to model sequential data and preserve information over long time intervals. Unlike conventional recurrent neural networks, LSTM incorporates memory cells and gating mechanisms that regulate the flow of information, enabling the network to learn long-term temporal dependencies more effectively.

The internal computations of an LSTM cell are governed by (4)-(9):

– Forget gate operation:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{4}$$

– Input gate is defined as (5):

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{5}$$

– The candidate cell state is computed as (6):

$$\tilde{\mathrm{C}}_\mathrm{t} = \tanh(W_C[h_{t-1}, x_t] + b_C) \tag{6}$$

– The updated cell state is obtained as (7):

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{\mathrm{C}}_t \tag{7}$$

– The output gate is calculated as (8):

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{8}$$

– The hidden state is determined as (9):

$$h_t = o_t \odot \tanh(C_t) \tag{9}$$

where x_t denotes the input vector at time step t, h_t represents the hidden state, C_t denotes the memory cell state, σ is the sigmoid activation function, and $\odot$ indicates element-wise multiplication. These gating mechanisms allow LSTM networks to learn long-term sequential dependencies within time series data.

2.3. Hybrid ARIMA–LSTM forecasting framework

The proposed hybrid forecasting framework combines statistical modeling with deep learning in a sequential two-stage process. ARIMA is first employed to explain the linear dynamics of the exchange rate series. The remaining residual sequence, which contains information not captured by the statistical model, is subsequently modeled using an LSTM network to learn nonlinear temporal relationships.

The residual sequence is then supplied to the LSTM network, which learns nonlinear dependencies that remain after the linear structure has been modeled. Let the observed series be expressed as (10).

$$Y_t = L_t + N_t \tag{10}$$

where: Y_t = observed exchange rate; L_t = linear component captured by ARIMA; and N_t = nonlinear component. After fitting the ARIMA model, the residual error is calculated as (11).

$$e_t = Y_t - \hat{\mathrm{Y}}_{\mathrm{ARIMA,t}} \tag{11}$$

The residual sequence e_t contains nonlinear patterns that are not explained by the ARIMA model. These residuals are then used as input to the LSTM neural network. The nonlinear residual component estimated by the LSTM model is expressed as (12).

$$\hat{\mathrm{Y}}_{\mathrm{LSTM,t}} = f(e_{t-1}, e_{t-2}, \dots, e_{t-k}) \tag{12}$$

The final forecast is obtained by combining the ARIMA prediction with the residual correction generated by the LSTM model:

$$\hat{\mathrm{Y}}_t = \hat{\mathrm{Y}}_{\mathrm{ARIMA,t}} + \hat{\mathrm{Y}}_{\mathrm{LSTM,t}}$$

where: $\hat{Y}_t$ = final hybrid forecast; $\hat{Y}_{\text{ARIMA,t}}$ = forecast produced by ARIMA model; and $\hat{Y}_{\text{LSTM,t}}$ = nonlinear residual forecast produced by LSTM model

3. METHOD

This section describes the dataset, preprocessing procedures, stationarity testing, hybrid model implementation, and evaluation metrics used to assess forecasting performance.

3.1. Data description

Monthly exchange rate data for four major foreign currencies against the Indian rupee, namely USD, GBP, JPY, and EUR, were used in this study. The dataset spans May 1966 to February 2025 and was obtained from the official database of the Reserve Bank of India (RBI). Table 1 presents the coverage, frequency, and number of observations for each currency. The data provide a long historical record that enables the investigation of exchange rate behaviour under different economic conditions.

Table 1. Exchange rate dataset coverage

Currency	Start date	End date	Frequency	Observations
USD	May 1966	Feb 2025	Monthly	706
GBP	May 1966	Feb 2025	Monthly	706
JPY	May 1966	Feb 2025	Monthly	706
EUR	Jan 1999	Feb 2025	Monthly	314

3.2. Data preprocessing

Before model development, the exchange rate time series were preprocessed to ensure consistency and reliability. The preprocessing stage included aligning time indices across currencies, handling missing observations, and converting the data into structured time-series format suitable for statistical and machine learning analysis. Data normalization was applied during LSTM training to improve convergence and learning stability.

3.3. Stationarity testing

Stationarity is an important prerequisite for ARIMA modeling because the statistical properties of the series should remain stable over time. The ADF test was therefore applied to evaluate the stationarity of each exchange rate series. The ADF test evaluates the presence of a unit root in the time series using the following regression:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t \quad (13)$$

where: Y_t represents the observed exchange rate at time t; Δ denotes the first difference operator; α is the intercept; βt represents the deterministic time trend; γ represents the coefficient used to test stationarity; and ε_t is the white noise error term.

If the calculated p-value is less than the chosen significance level, the null hypothesis of a unit root is rejected, indicating that the time series is stationary. When non-stationarity was detected, first-order differencing was applied to transform the series into stationary form before fitting ARIMA models.

3.4. Hybrid model implementation

The hybrid forecasting model integrates ARIMA and LSTM models in a two-stage framework. First, ARIMA models are fitted to the stationary exchange rate series to capture linear temporal dependencies. Residual errors from the ARIMA forecasts represent nonlinear patterns that are not explained by the statistical model. These residuals are then used to train the LSTM network, which learns nonlinear temporal relationships. The final forecast is obtained by combining the ARIMA prediction with the LSTM-predicted residual component. The final hybrid forecasting equation is expressed as:

$$\hat{Y}_t = \hat{Y}_{\text{ARIMA,t}} + \hat{Y}_{\text{LSTM,t}}$$

where: $\hat{Y}_t$ represents the final hybrid forecast; $\hat{Y}_{\text{ARIMA,t}}$ represents the ARIMA model forecast; and $\hat{Y}_{\text{LSTM,t}}$ represents the nonlinear residual forecast produced by the LSTM model.

3.5. Performance evaluation metrics

Forecast accuracy was evaluated using root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). These metrics measure the deviation between predicted and actual values, with lower values indicating better predictive performance.

– The RMSE metric is defined as (14):

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2} \quad (14)$$

– The MAE metric is defined as (15):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \quad (15)$$

– The MAPE metric is defined as (16):

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \quad (16)$$

where: Y_t represents the observed exchange rate; $\hat{Y}_t$ represents the predicted exchange rate; and n represents the number of observations. These metrics provide quantitative measures of forecasting accuracy and allow comparison between the ARIMA model, LSTM model, and the proposed hybrid ARIMA–LSTM framework.

4. RESULTS AND DISCUSSION

This section presents the empirical results obtained from the statistical and hybrid forecasting models. The analysis includes stationarity testing, ARIMA model identification, hybrid ARIMA–LSTM forecasting performance, and comparative evaluation using error metrics.

4.1. Stationarity analysis

The stationarity of each exchange rate series was evaluated using the ADF test. Results indicated that the original series were non-stationary because the p-values exceeded the 0.05 significance level. After applying first-order differencing, the p-values dropped below 0.05 for all currencies, confirming that the differenced series are stationary. Table 2 presents the ADF test statistics and corresponding p-values for both the original and differenced series. The results demonstrate that all four exchange rate series become stationary after applying first-order differencing, which implies that the integration order for the ARIMA model is $d = 1$.

These findings confirm that the exchange rate series exhibit non-stationary behavior in their original form but become stationary after first-order differencing. Consequently, the ARIMA models used in this study incorporate a differencing order of $d = 1$ for all currencies.

Table 2. ADF test results before and after differencing

Currency	ADF statistic (original)	p-value	ADF statistic (differenced)	p-value	Stationary after differencing
USD	1.5168	0.9976	-22.7169	0.0000	Yes
GBP	0.0450	0.9621	-22.8820	0.0000	Yes
JPY	-0.6706	0.8542	-6.5399	0.0000	Yes
EUR	-0.9160	0.7826	-14.6864	0.0000	Yes

4.2. Identification of ARIMA model parameters

After achieving stationarity through first-order differencing, the autocorrelation function (ACF) and partial ACF (PACF) plots were examined to determine appropriate ARIMA model parameters. The ACF plot illustrates the correlation between observations across different time lags, whereas the PACF plot shows the direct correlation at each lag after accounting for the influence of the intervening lags.

Figure 1 illustrates the ACF plot of the differenced USD exchange rate series. The plot shows a noticeable spike at lag 1 followed by correlations that quickly decline and fall within the confidence bounds. This pattern suggests that the influence of past shocks diminishes rapidly, indicating limited moving-average behavior in the series. Figure 2 presents the PACF plot of the differenced USD exchange rate series. The

PACF plot exhibits a significant spike at lag 1, while the remaining lags lie within the confidence interval. This behavior indicates the presence of a first-order autoregressive component in the time series.

Based on the combined interpretation of the ACF and PACF plots, the autoregressive order was identified as $p = 1$, while the moving-average order was determined as $q = 0$. Since stationarity was achieved after first-order differencing, the integration order is $d = 1$. Therefore, the ARIMA(1,1,0) model was selected as a suitable baseline model for forecasting the exchange rate series.

The same procedure was applied to the other currency exchange rate series (GBP/INR, JPY/INR, and EUR/INR). Similar correlation patterns were observed, indicating that ARIMA(1,1,0) provides a consistent and appropriate structure for modeling the exchange rate dynamics across all currencies considered in this study. The suggested ARIMA model structures are summarized in Table 3. The ACF and PACF patterns across the four currencies show similar lag behavior, indicating that the ARIMA(1,1,0) specification provides a consistent baseline model for the exchange rate series analyzed in this study.

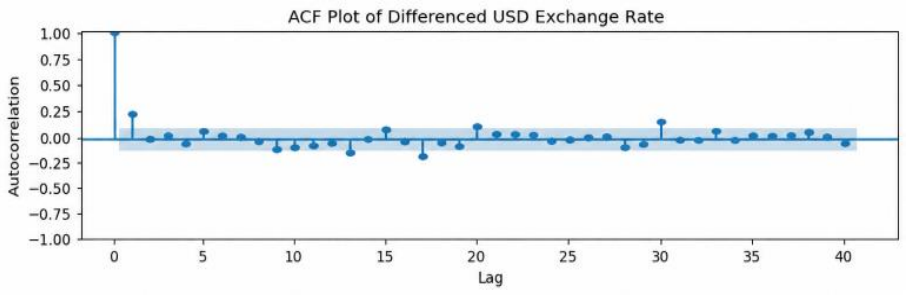


Figure 1. ACF plot of the differenced USD/INR exchange rate series

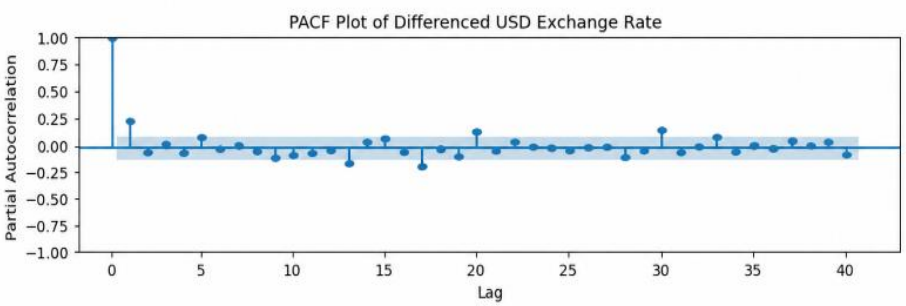


Figure 2. PACF plot of the differenced USD/INR exchange rate series

Table 3. Suggested ARIMA model structures based on ACF and PACF analysis

Currency	Suggested ARIMA model
USD	ARIMA(1,1,0)
GBP	ARIMA(1,1,0)
JPY	ARIMA(1,1,0)
EUR	ARIMA(1,1,0)

4.3. ARIMA model estimation

After identifying the appropriate model structure through ACF and PACF analysis, the ARIMA(1,1,0) model was used as the baseline model for exchange rate forecasting, and parameter estimation is illustrated using the USD/INR series. The estimation provides parameter values and diagnostic statistics that describe the adequacy of the fitted model.

The ARIMA(1,1,0) specification includes a first-order autoregressive component applied to the differenced series. The estimated AR(1) coefficient is 0.2256, indicating that the previous period's differenced exchange rate has a moderate positive influence on the current observation. The coefficient is statistically significant, as indicated by the z-value of 10.1880 and a p-value below 0.001, confirming the presence of short-term temporal dependence in the exchange rate movements.

Model adequacy was further evaluated using the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Lower values of these criteria generally indicate a better model fit while penalizing model complexity. The estimated model produced an AIC value of 1378.4575 and a BIC value of 1387.5482, suggesting that the ARIMA(1,1,0) specification provides an adequate representation of the linear structure in the exchange rate time series. The estimated model parameters and diagnostic statistics are summarized in Table 4.

Table 4. Model diagnostics and estimated parameters of the ARIMA(1,1,0) model

Type	Criterion/parameter	Value/estimate	Std. error	z-value	p-value
Model criterion	AIC	1378.4575	-	-	-
Model criterion	BIC	1387.5482	-	-	-
Parameter	AR(1)	0.2256	0.0221	10.1880	0.0000

4.4. Hybrid ARIMA–LSTM forecasting results

Forecasting performance was evaluated using a hybrid ARIMA–LSTM framework. First, the ARIMA(1,1,0) model was applied to capture the linear structure of the exchange rate series and generate baseline forecasts. The residual errors from the ARIMA model were then modeled using an LSTM neural network to capture nonlinear dependencies in the data. The final hybrid forecast was obtained by combining the ARIMA predictions with the LSTM residual forecasts.

Table 5 presents the forecasting performance of the baseline ARIMA model and the proposed hybrid ARIMA–LSTM model. The results show that the hybrid model achieves lower error values across all evaluation metrics. In particular, the hybrid model produced an RMSE of 1.5863, a MAE of 1.2425, and a MAPE of 1.7691%, indicating improved predictive accuracy compared to the standalone ARIMA model.

The forecasting performance of the proposed hybrid ARIMA–LSTM model is further illustrated in Figure 3, which compares the actual exchange rate values with the predicted values generated by the hybrid model. The hybrid ARIMA–LSTM forecast closely follows the observed exchange rate trajectory, indicating improved predictive performance.

Table 5. Forecasting performance comparison

Model	RMSE	MAE	MAPE (%)
ARIMA(1,1,0)	1.9214	1.5342	2.1437
Hybrid ARIMA–LSTM	1.5863	1.2425	1.7691

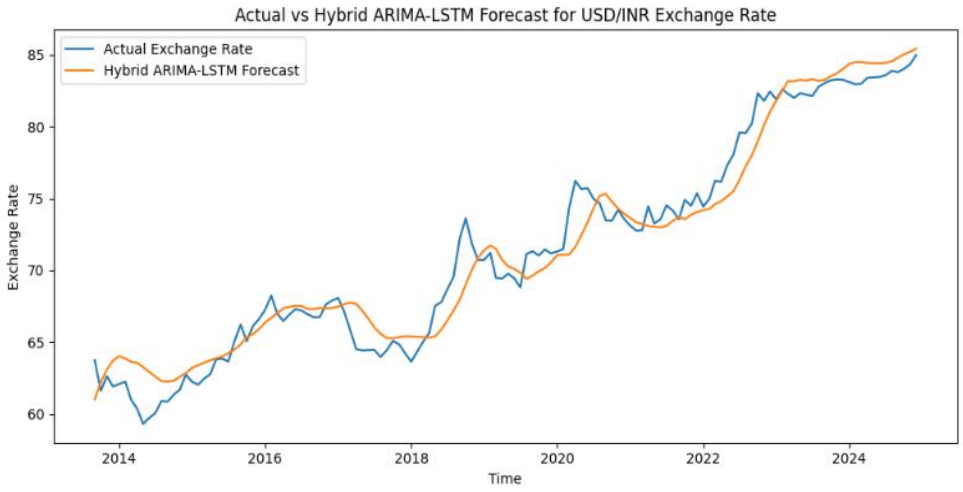


Figure 3. Actual versus hybrid ARIMA–LSTM forecast for the USD/INR exchange rate series

5. CONCLUSION

This study investigated the forecasting of INR exchange rates using a hybrid ARIMA–LSTM modeling framework. The stationarity of the exchange rate series was first examined using the ADF test,

which confirmed that all currency series became stationary after first-order differencing. Based on the analysis of autocorrelation and partial autocorrelation patterns, an ARIMA(1,1,0) model was identified as an appropriate baseline model for capturing the linear dynamics of the exchange rate series. To enhance forecasting accuracy, a hybrid approach was implemented by combining the ARIMA model with a LSTM neural network. In this framework, the ARIMA model captures the linear component of the time series, while the LSTM model learns nonlinear patterns present in the residual sequence. Empirical results demonstrate that the hybrid ARIMA–LSTM model achieves lower forecasting errors compared with the standalone ARIMA model, as reflected by improvements in RMSE, MAE, and MAPE metrics. The proposed ARIMA–LSTM framework provides a reliable approach for modeling complex financial time series and can be extended to other macroeconomic forecasting applications.

FUNDING INFORMATION

The authors declare that this research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. This work was carried out as part of the doctoral research of the first author.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Balasubramanian Subramanian	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	
Natarajan M	✓	✓		✓	✓	✓				✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this study. Authors state no conflict of interest.

DATA AVAILABILITY

The data used in this study were obtained from publicly available government and statistical data portals, including IndiaStat (https://www.indiastat.com) and the Government of India Open Data Portal (https://www.data.gov.in). The processed dataset and derived data supporting the findings of this study are available from the corresponding author upon reasonable request.

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