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# Determinants of Inbound International Tourism Demand in India: An Econometric Analysis

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## Abstract
This study investigates the key determinants of inbound international tourism demand in India using econometric analysis. Employing time-series data ARDL, the model examines the role of foreign tourist, Indian tourist, foreign direct investment and exchange rates in shaping tourist arrivals. The results reveal that income and trade openness positively influence tourism demand, while high relative prices act as a deterrent. Exchange rate stability emerges as a crucial factor in attracting international tourists. The findings highlight the interdependence between economic factors and tourism flows. Policy implications suggest enhancing infrastructure, ensuring price competitiveness, and promoting India's image to sustain long-term growth in inbound tourism

**Keywords:** tourism demand, India, ARDL, cointegration, ECM,

## 1. Introduction
International tourism is widely recognized as a powerful engine of economic development, particularly for emerging economies that possess rich cultural resources, diverse natural landscapes, and rapidly expanding service sectors. Tourism contributes significantly to gross domestic product (GDP), foreign exchange reserves, and employment generation, both directly in the hospitality and aviation industries and indirectly through linkages with agriculture, handicrafts, transport, and retail services. For countries such as India, which holds a unique position in the global tourism market, international visitor inflows are shaped by multiple structural and cyclical forces. These include demand-side conditions in source countries, supply-side enhancements in aviation and hospitality infrastructure, institutional reforms in visa and taxation regimes, as well as exogenous shocks ranging from financial crises to pandemics (UNWTO, 2023; Das & Dirienzo, 2010). Understanding how these diverse drivers interact in both the short and long run is crucial for designing resilient tourism policies that support growth and stability. India has historically leveraged its cultural diversity, heritage monuments, spiritual traditions, and wellness offerings to attract global travelers (Chakrabarti & Ghosh, 2020). Over the past two decades, the country has also benefited from significant investments in airport modernization, low-cost carriers, and improved connectivity to secondary cities, thereby expanding its tourism footprint beyond the traditional "Golden Triangle" of Delhi–Agra–Jaipur (Ministry of Tourism, Government of India, 2023). These structural improvements have coincided with pro-tourism policy measures such as the introduction of e-Visa facilities for more than 160 nationalities, liberalized open-skies agreements, and the rationalization of goods and services tax (GST) on hospitality services. As a result, inbound arrivals showed a consistent

upward trajectory until the disruption caused by COVID-19, which underscored the vulnerability of international travel demand to global shocks (Nicola et al., 2020). The determinants of inbound tourism demand are multifaceted. On the macroeconomic front, the income levels of source markets play a decisive role, as rising disposable incomes in advanced and emerging economies directly translate into greater propensity to travel abroad (Song et al., 2010). Price and exchange rate competitiveness are equally critical. Tourists are sensitive to the relative cost of goods and services in a destination, which means that fluctuations in bilateral exchange rates, inflation differentials, and purchasing power parity adjustments can alter the attractiveness of India compared to rival destinations in Asia (Dritsakis, 2004). Transport capacity and network centrality further mediate accessibility. The rapid expansion of airline routes, code-sharing agreements, and hub connectivity enhances convenience and reduces the generalized cost of travel, stimulating demand from both established and new markets (Goh et al., 2012).

Institutional and policy variables are also essential to understand. Visa facilitation reforms, such as India's rollout of e-Visa categories (tourist, business, medical), have demonstrably boosted arrivals from key partner nations by reducing administrative barriers (Neumayer, 2010). Similarly, tax structures like GST influence the cost structure of accommodation and packaged tours, indirectly shaping price competitiveness. Beyond economic and policy factors, perceptions of safety, political stability, and destination sentiment weigh heavily in travel decisions. Episodes of terrorism, geopolitical tensions, or health scares can temporarily dampen demand, while positive media coverage or global events hosted by India can enhance its appeal (Fourie & Santana-Gallego, 2011). While existing literature has investigated tourism demand using various econometric approaches, important gaps remain. Much of the early work on India has focused on simple elasticity models linking arrivals to income and relative prices (Kulendran & Witt, 2001). More recent studies have extended this to include exchange rate volatility and infrastructure, but few have comprehensively combined macroeconomic, institutional, transport, and sentiment-based variables into a unified framework. Moreover, shocks such as the global financial crisis of 2008 and the COVID-19 pandemic highlight the need to explicitly model structural breaks, asymmetries, and nonlinearities in tourism demand equations (Narayan, 2005). This paper addresses these limitations by employing two complementary empirical strategies. The first empirical contribution is the construction of a comprehensive determinant set for India's inbound tourism demand. This includes: (i) macroeconomic drivers such as real GDP per capita in origin markets; (ii) price competitiveness proxied by relative consumer price indices and real effective exchange rates; (iii) bilateral exchange rate levels and volatility measures; (iv) supply-side indicators such as available airline seat capacity and network connectivity indices; (v) institutional and policy reforms such as the e-Visa rollout, open skies agreements, and GST changes; and (vi) risk and sentiment indicators including safety perception indices, geopolitical conflict dummies, and Google Trends data on travel interest. By encompassing this wide set of drivers, the analysis moves beyond narrow price-income frameworks to capture the multidimensional reality of international tourism. Second, the paper applies dual econometric methodologies to strengthen inference. At the aggregate level, we implement autoregressive distributed lag (ARDL) and nonlinear ARDL (NARDL) models using India's inbound arrivals as the dependent variable, enabling us to identify both long-run equilibrium relationships and short-run dynamics, as well as possible asymmetric responses to exchange rate appreciations versus depreciations. At the bilateral source-market level, we employ a panel ARDL with pooled mean group (PMG) estimation, which allows for long-run homogeneity across countries while accommodating short-run heterogeneity in adjustment speeds and shocks. This dual strategy thus balances aggregate insights with disaggregated nuance, enhancing the robustness of the findings (Pesaran et al., 1999; Pesaran & Shin, 1998). Third, we adopt rigorous time-series and panel econometric procedures to address statistical challenges in tourism data. We conduct unit root tests with structural break adjustments, cointegration analysis, and multiple break detection to ensure valid inference. By integrating modern econometric tools suited to non-stationary and shock-prone data, we aim to provide more credible evidence on the determinants of inbound tourism to India. This methodological contribution is particularly important in light of criticisms that traditional demand models often ignore nonlinearity, volatility, and structural instability (Song & Li, 2008). The remainder of the study is structured as follows. Section 2 provides a critical review of the tourism demand literature, highlighting theoretical models and empirical evidence from both global and India-specific contexts. Section 3 develops a conceptual framework and outlines hypotheses regarding the impact of income, prices, transport, policy, and risk on inbound arrivals. Section 4 describes the data sources, variable definitions, and summary statistics. Section 5 details the econometric methodologies, including ARDL. Section 6 presents empirical findings, while Section 7 offers robustness checks and diagnostic results. Section 8 discusses policy implications for sustainable tourism development in India, and Section 9 concludes.

## 2. Literature Review

### 2.1 Foundations of Tourism Demand Modelling

The study of international tourism demand has long been grounded in the identification of core economic and non-economic determinants. Classic survey contributions such as Crouch (1994), Lim (1997), Song and Witt (2000), and Song and Li (2008) provide comprehensive syntheses of the variables that consistently drive inbound travel flows. These include macroeconomic conditions in source markets (especially disposable income), relative price levels between origin and destination, travel costs (with transport costs serving as proxies), and the availability of substitute destinations. Beyond these economic fundamentals, qualitative and perceptual variables—such as perceptions of safety, political stability, destination image, and the ease of visa acquisition—are repeatedly highlighted as important in shaping demand.

tourism demand modelling has steadily evolved alongside advances in econometrics. Earlier approaches predominantly employed single-equation time-series models using ordinary least squares or basic autoregressive distributed lag structures. However, the increasing availability of long time-series data, coupled with recognition of non-stationarity in tourism variables, led to the widespread application of cointegration techniques. Error-correction models, in particular, became standard because they capture both the long-run equilibrium relationships among variables and the short-run adjustments back to equilibrium after shocks.

A further innovation was introduced by Pesaran, Shin, and Smith (2001), who developed the autoregressive distributed lag (ARDL) bounds testing approach. This framework allows researchers to model relationships among variables that are integrated of mixed orders, i.e., I(0) or I(1). In practice, ARDL has become a preferred tool in tourism demand research because tourism time-series often display mixed integration orders. More recently, attention has turned toward nonlinear and asymmetric effects. This is important because tourist behavior is often asymmetric; for example, a depreciation of the host country's currency may significantly boost demand, but an equivalent appreciation may not lead to a proportionate decline.

### 2.2 Gravity and Multi-Origin Models

While time-series analyses focus on a single destination or origin, multi-country and multi-market studies frequently employ gravity models. Adapted from international trade theory, gravity models assume that flows of goods or people increase with economic "mass" (i.e., the income of origin markets) and decline with distance or other impediments that raise travel costs. Applied to tourism, the gravity framework suggests that tourist arrivals to a destination expand with higher income levels in origin countries but contract when relative prices, distance, or institutional frictions (such as visa requirements) are high (Proença & Soukiazis, 2008; De Vita, 2014).

To operationalize these models in an econometric setting, scholars have relied on panel cointegration approaches, including those developed by Pedroni (1999, 2004) and Kao (1999). These techniques account for long-run relationships across heterogeneous countries or regions while also allowing for cross-sectional dependence. A further advancement is the Pooled Mean Group (PMG) estimator by Pesaran, Shin, and Smith (1999). PMG is particularly suitable for tourism data because it imposes long-run homogeneity (consistent elasticities across source markets) while allowing for heterogeneity in the short-run dynamics. This balances theoretical coherence with empirical flexibility. Consequently, gravity-style panel models using PMG estimation have become prominent in comparative tourism studies that assess how demand from multiple origins responds to macroeconomic drivers, exchange rates, and policy changes.

### 2.3 Price, Exchange Rates, and Uncertainty

Relative prices and exchange rates represent some of the most critical variables influencing international tourism flows, as they directly affect the affordability of travel. Dwyer, Forsyth, and Rao (2000) emphasize the role of relative price competitiveness, while earlier reviews by Crouch (1994) underscore how exchange-rate changes translate into shifts in demand. Webber (2001) empirically demonstrated that depreciation of a destination's currency often stimulates inbound arrivals, as foreign tourists perceive the destination to be cheaper.

However, it is not merely the level of exchange rates that matters, but also their volatility. Exchange-rate instability generates uncertainty, which discourages travel planning and can deter risk-averse tourists. Studies that employ volatility measures derived from Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models have confirmed the negative effects of uncertainty (Santana-Gallego et al., 2016). Beyond exchange-rate volatility, broader forms of uncertainty—such as global financial crises, health pandemics, or geopolitical risks—also suppress tourism demand.

An important line of inquiry is the possibility of asymmetric responses. For example, a currency depreciation may strongly boost demand by enhancing affordability, but an appreciation of similar magnitude may have a smaller deterrent effect if travelers view India as a culturally unique or "must-see" destination. NARDL models are well-suited to capture such nonlinearities. Thus, while the basic premise that price competitiveness matters is well established, modern literature has expanded to consider the subtler dynamics of volatility, uncertainty, and asymmetric effects.

### 2.4 Connectivity, Visa Policy, and Perceptions

Accessibility and connectivity have also emerged as central determinants of inbound tourism. Air transport supply, including variables such as seat capacity, flight frequency, and network centrality, effectively lowers generalized travel costs and makes destinations more accessible (Graham, Papatheodorou, & Forsyth, 2010). With the expansion of international aviation, the availability of direct connections has become a critical factor in shaping tourist choices, particularly for long-haul destinations such as India.

Policy interventions around visa regimes are another determinant that significantly influences demand. Neumayer (2010) and subsequent analyses by the UNWTO show that more relaxed visa policies—such as e-Visas or visas on arrival—can substantially increase arrivals by lowering administrative and psychological barriers to travel. Empirical studies confirm that visa facilitation elasticities are often large, underscoring the importance of such policies in tourism competitiveness.

Perceptions also play an important role. Factors such as perceived safety, public health risks, political stability, and overall destination image can either reinforce or undermine the quantitative drivers of demand. Prideaux (2005) notes that negative safety perceptions can quickly deter international visitors, while Ritchie and Jiang (2019) discuss how destinations recover from crises such as natural disasters or pandemics. In this context, risk and sentiment variables, including online search interest, conflict dummies, or safety indices, can provide valuable insights into the short-term fluctuations in tourism demand.

### 2.5 India-Focused Evidence

The Indian case has attracted growing scholarly attention given the country's rich cultural assets, diverse tourism offerings, and rising prominence in the global tourism market. Empirical studies focusing on India highlight several consistent themes. First, income growth in key source markets, such as the United States, the United Kingdom, and other OECD economies, is a strong driver of inbound tourism demand. Second, relative price competitiveness matters; both consumer price differentials and exchange-rate fluctuations shape affordability and thereby arrivals. Third, policy initiatives—especially the introduction of e-Visa schemes, greater openness in aviation agreements, and reductions in service taxes—have demonstrable positive impacts on arrivals.

However, findings vary depending on methodology, time period, and variable definitions. Some studies highlight strong price and exchange-rate effects, while others find them weaker once structural breaks or global shocks are accounted for. There is also limited evidence on asymmetry in exchange-rate effects, with few studies systematically testing whether depreciations and appreciations exert different magnitudes of impact. Likewise, although exchange-rate volatility is a plausible deterrent, its effect in the Indian context remains underexplored. Finally, the role of digital variables such as online search interest (e.g., Google Trends) in predicting inbound demand to India remains largely absent from the literature, despite growing evidence elsewhere of their predictive power.

Taken together, this review indicates that while the determinants of international tourism demand are well established globally, there remain notable gaps in the Indian case. Specifically, evidence on asymmetry, volatility, and digital proxies of sentiment is scarce. Addressing these gaps through robust econometric approaches such as ARDL, NARDL, and gravity-style panel models can advance understanding of inbound tourism to India and provide actionable insights for policy.

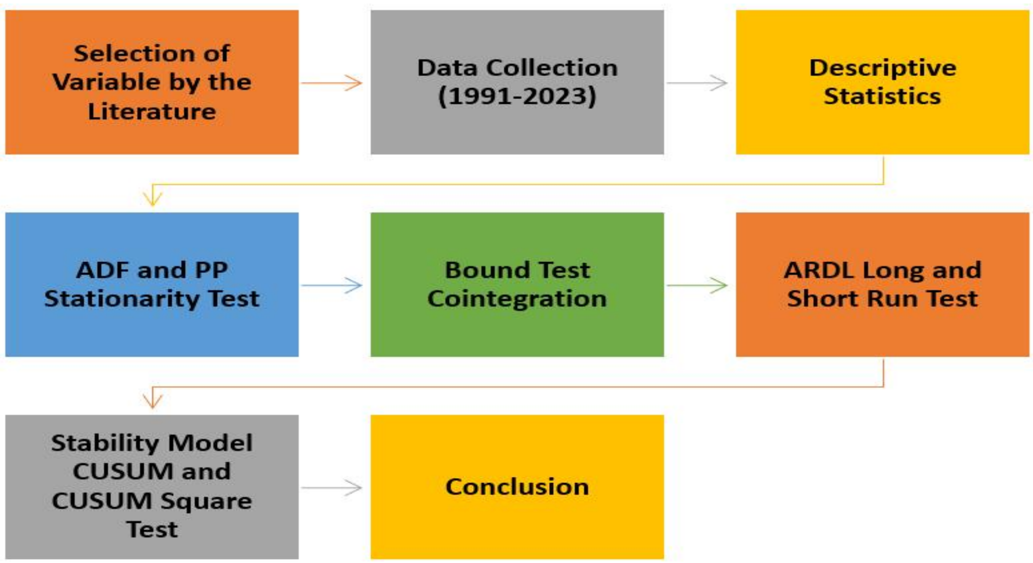

Fig. 1, Framework of the study

## 3. Research Methodology:

The research methodology represents the theoretical framework that guides the identification and selection of variables, as well as the collection of relevant data for the study. It enables the researcher to critically evaluate the overall reliability, validity, and effectiveness of the investigation. Methodological procedures typically involve defining the research problem, gathering data, and employing tools such as surveys, interviews, and other appropriate techniques.

In this study, secondary data has been utilized. The required information was obtained from reliable sources including the *World Development Indicators (WDI/ World bank)*. The analysis covers a period of 32 years, spanning from 1991 to 2023.

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**Selected Variables and their definitions**

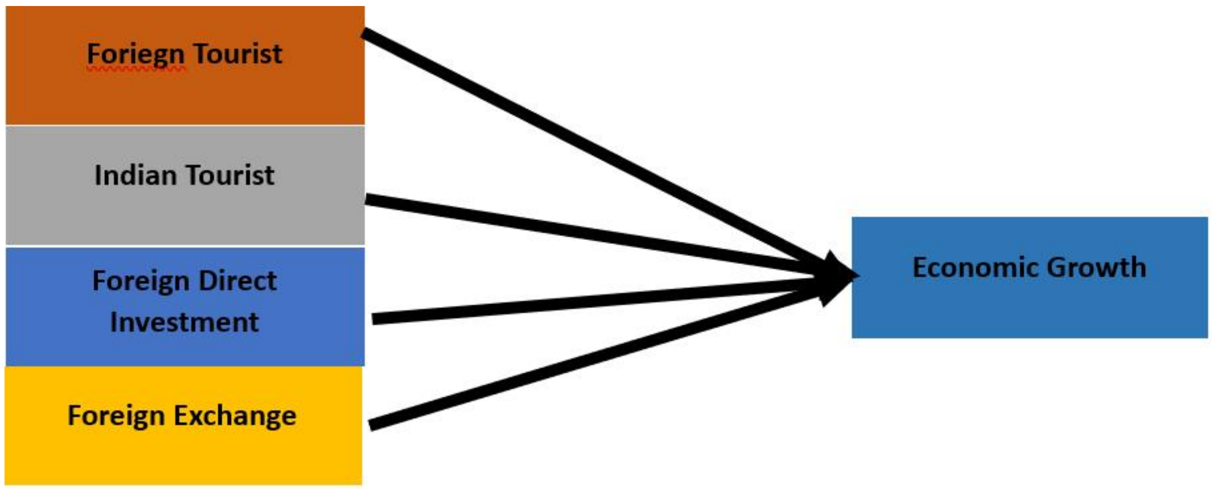



Figure 2, Dependent and independent variable of the study

**Table 1: Variable names and description**

| Symbol | Variable Name | Measurement Unit | Source |
|---|---|---|---|
| GDP | Gross Domestic Product | Annual % growth | WB |
| FT | Foreign Tourist | US dollar | WB |
| IT | Indian Tourist | Indian rupees | WB |
| FDI | Foreign Direct Investment | Foreign direct investment, net inflows (% of GDP) | WB |
| FE | Foreign Exchange | Official exchange rate (LCU per US$, period average) | WB |

**Sources;** World Bank

**Hypothesis Formulation**
H0 =There is no Determinants inbound tourism in India.
H1 = Determinants inbound tourism in India.

### 3.1 Econometric Model:

In order to describe the relationship between rice production, rainfall, maximum temperature, minimum temperature, and mean temperature this study uses the following equation,

$$LNGDP_t = \alpha + \beta_1 LNFT_t + \beta_2 LNIT_t + \beta_3 LNFDI_t + \beta_4 LNFE\varepsilon_t \qquad (1)$$

In this specified model, LNRP represents the natural logarithm of the dependent variable, while LNFT, LNIT, LNFDI and LNFE represent the natural logarithms of foreign tourist, indian tourist, foreign direct investment and foreign exchang respectively. The coefficients $\alpha$, $\beta_1$, $\beta_2$, $\beta_3$ and $\beta 4$ represent the constant and different elasticities, and $\varepsilon_t$ denotes the error terms.

To test for unit roots, the Augmented Dickey–Fuller (ADF) test and Phillips–Perron (PP) test are conducted separately, incorporating intercept and trend. The lag length selection is determined using the Schwarz information criteria (SIC), with lag lengths of 1 and 3 considered appropriate. The ADF test addresses serial correlation in the error term by including the lagged difference of the dependent variable. The ADF unit root equation is expressed in (2), while the formula for the Phillips–Perron unit root test is provided in (3).

$$\Delta Yt = \alpha Y_{t-1} + x_t^{l}\delta + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + V_t \ldots\ldots\ldots (2)$$

$$t_{\propto} = t_{\propto}\left(\frac{y_0}{t_0}\right)^{1/2} - \frac{T(t_0 - y_0)(Se(\propto))}{2 f_0^{1/2} S} \qquad (3)$$

The equation employed for ARDL bounds testing in the model, as outlined by Ali, et., al., 2022: Ansari et al. (2022, 2023; 2024; 2024; 2025)), and Khan et al. (2024), is denoted as Equation (4).

$$\Delta LNGDP_t = \gamma_0 + \sum_{i=1}^{n} \gamma_{1i} LNGDP_{t-1} + \sum_{i=1}^{n} \gamma_{2i} LNFT_{t-1} + \sum_{i=1}^{n} \gamma_{3i} LNIT_{t-1} + \sum_{i=1}^{n} \gamma_{4i} LNFDI_{t-1} + \sum_{i=1}^{n} \gamma_{5i} LNFE_{t-1} + \varepsilon_t \ldots$$

The long-run ARDL model to be estimated is presented in Equation (5).

$$\Delta LNGDP = \beta_0 + \sum_{i=1}^{q} \omega_1 LNGDP_{t-1} + \sum_{i=1}^{q} \omega_2 LNFT_{t-1} + \sum_{i=1}^{q} \omega_3 LNIT_{t-1} + \sum_{i=1}^{n} \omega_4 LNFDI_{t-1} + \sum_{i=1}^{n} \omega_5 LNFE_{t-1} + \varepsilon_t \ldots$$

In Equation (5), ω represents the long-run variance of variables. The short-run ARDL model incorporating the error correction term is expressed as follows:

$$\Delta LNGDP_t = \beta_0 + \sum_{i=1}^{q} \pi_1 \Delta LNGDP_{t-1} + \sum_{i=1}^{q} \pi_2 \Delta LNFT_{t-1} + \sum_{i=1}^{q} \pi_3 \Delta LNIT_{t-1} + \sum_{i=1}^{q} \pi_4 \Delta LNFDI_{t-1} + \sum_{i=1}^{q} \pi_5 \Delta LNFE_{t-1}$$

In Equation (6), π represents the short-run variability of the variables, while ECT denotes the error correction term, indicating the speed of adjustment to disequilibrium. The Error Correction Term (ECT) was estimated with a coefficient ranging between -1 and 0. Explanatory variables' impact on dependent variables was assessed through graphical analysis. Diagnostic tests were conducted to assess model stability, including the Breusch–Godfrey LM test for serial correlation, the Breusch–Pagan–Godfrey test and ARCH test for heteroscedasticity, the Ramsey RESET test for correct specification, and the Jarque–Bera test for evaluating the normal distribution of residuals. Structural stability was examined using two approaches: cumulative sums of recursive residuals (CUSUM) and cumulative sums of squares of recursive residuals (CUSUMSQ).

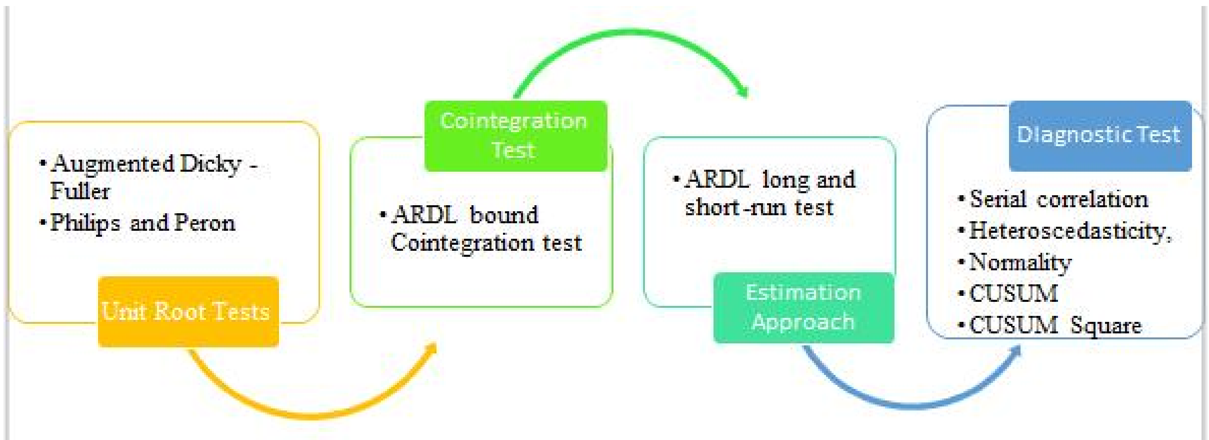



Figure 3, Framework Research Methodology

## 4. Result and Discussion

### RADAR Descriptive Statistics

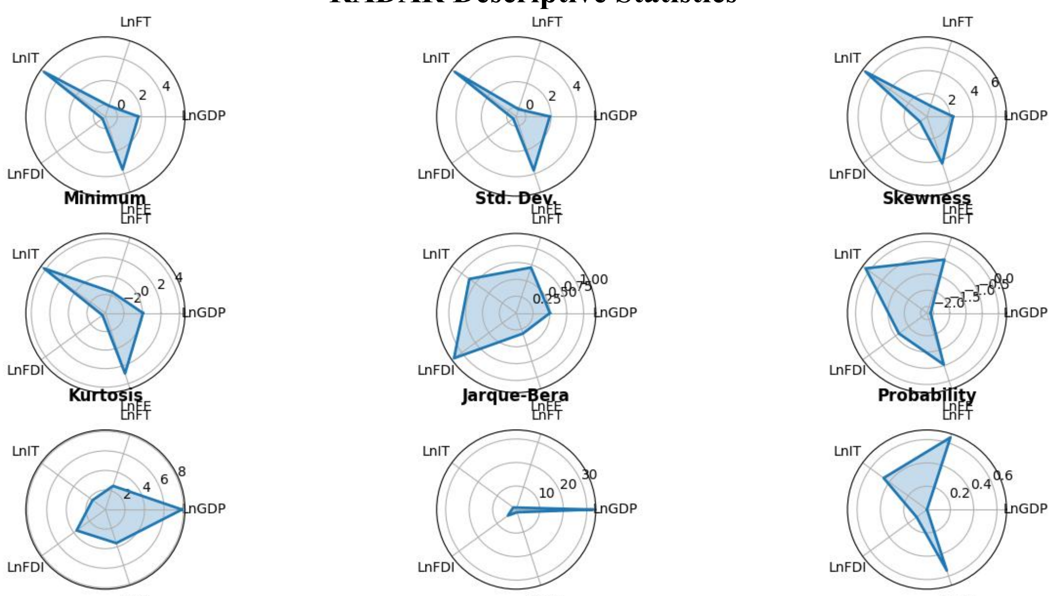


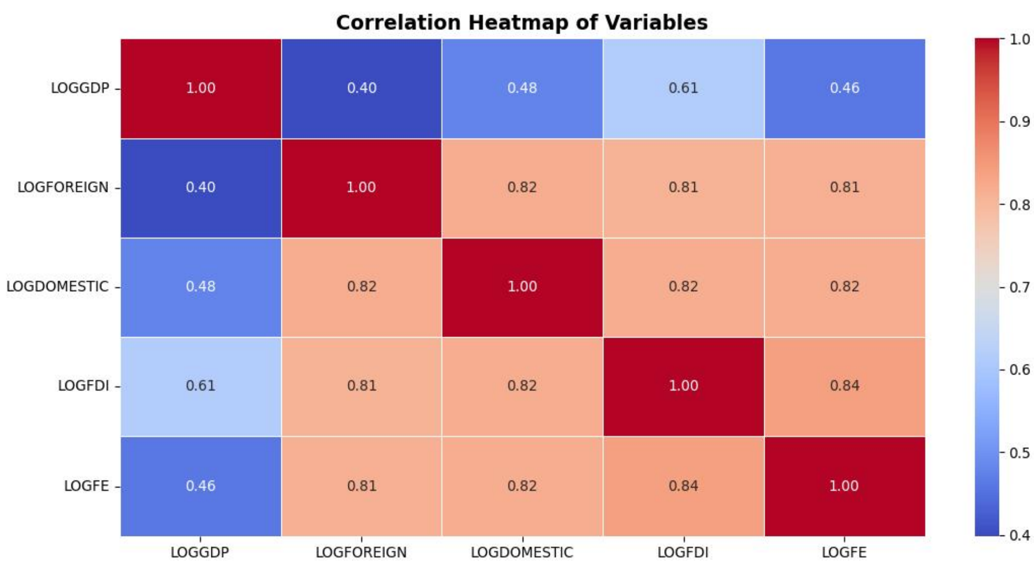

figure 4, Calculated by Author through python Software

Figure 4, Mean (average): Among all variables, LnIT records the highest mean (5.32), indicating consistently larger values. LnFDI, on the other hand, shows a negative mean (–0.69), reflecting generally low or negative logged flows. LnFE (3.63) and LnGDP (1.75) maintain positive and steady averages, while LnFT (–0.05) remains close to zero, suggesting balanced fluctuations.

Median: The median values are close to their respective means, pointing to limited asymmetry. LnIT (5.25) and LnFE (3.72) exhibit the strongest central tendencies, whereas LnFDI again reflects a negative median (–0.47). Maximum and Minimum: LnIT displays the widest range, with values stretching from 4.20 to 6.64, signifying substantial growth. LnFDI fluctuates heavily, spanning –3.60 to 0.75. LnGDP shows moderate stability (0.06–2.27), while LnFE (2.86–4.30)

also remains within a relatively stable band.Standard Deviation: The highest variability is observed in LnFDI (1.14), whereas LnFE (0.32) demonstrates the greatest stability. LnGDP, LnFT, and LnIT fall within moderate levels of dispersion. Skewness; LnGDP (–2.08) shows strong negative skewness, indicating a long left tail. LnFDI (–1.12) also leans negatively, while LnFT (–0.47) and LnFE (–0.53) are only mildly skewed. LnIT (0.14) is nearly symmetric.
Kurtosis: LnGDP (7.83) is highly leptokurtic, meaning its distribution is sharply peaked with heavy tails. LnFT (2.54) and LnFE (3.61) are close to the normal distribution, while LnIT (1.63) is relatively flat (platykurtic). LnFDI (3.63) is slightly peaked.

**Table 2: Results of Correlation Matrix**




Calculated by through Python

Table, 2 LOGGDP has moderate positive correlations with the other variables, ranging from 0.40 with LOGFOREIGN to 0.61 with LOGFDI. This indicates that GDP growth is positively associated with foreign trade, domestic activity, FDI, and financial expansion, but the strength of the relationship is not as strong as among the other variables. LOGFOREIGN is strongly correlated with LOGDOMESTIC (0.82), LOGFDI (0.81), and LOGFE (0.81). This suggests that foreign sector activities move closely with domestic output, investment, and financial elements. LOGDOMESTIC shows consistently high correlations with all other variables, particularly LOGFE (0.82) and LOGFDI (0.82), reflecting strong interlinkages between the domestic economy, financial expansion, and foreign investment. LOGFDI has the highest overall associations, with correlations above 0.80 with LOGFOREIGN, LOGDOMESTIC, and LOGFE, highlighting the crucial role of FDI as a connecting factor between domestic, foreign, and financial sectors. LOGFE also demonstrates strong correlations with the other variables (above 0.81 except for GDP at 0.46), indicating that financial expansion is deeply integrated with domestic production, foreign trade, and FDI flows.

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**Table 3: Results of ADF and PP Unit root test**

**UNIT ROOT TEST TABLE (ADF)**

| **At Level** | | | | **at First Difference** | | |
|---|---|---|---|---|---|---|
| **Variable** | **t-Statistic** | **Prob.** | **Variable** | **t-Statistic** | **Prob.** | **Decision** |
| **LnGDP** | -0.97 | 0.29 | d(LnGDP) | -10.73 | 0.00 | I(I) |
| **LnFT** | -2.56 | 0.01 | d(LnFT) | -4.19 | 0.00 | I(0) |
| **LnIT** | 1.77 | 0.98 | d(LnIT) | -4.68 | 0.00 | I(I) |
| **LnFDI** | -2.59 | 0.01 | d(LnFDI) | -5.91 | 0.00 | I(0) |
| **LnFE** | 3.56 | 1.00 | d(LnFE) | -4.38 | 0.00 | I(I) |
| | | | **Unit root test PP** | | | |
| **At Level** | | | **At First Difference** | | | |
| **Variable** | **t-Statistic** | **Prob.** | **Variable** | **t-Statistic** | **Prob.** | |
| **LnGDP** | -0.72 | 0.40 | d(LnGDP) | -10.83 | 0.00 | I(I) |
| **LnFT** | -2.58 | 0.01 | d(LnFT) | -4.12 | 0.00 | I(0) |
| **LnIT** | 2.85 | 0.98 | d(LnIT) | -4.74 | 0.00 | I(I) |
| **LnFDI** | -2.71 | 0.01 | d(LnFDI) | -5.92 | 0.00 | I(0) |
| **LnFE** | 2.73 | 0.78 | d(LnFE) | -4.39 | 0.00 | I(I) |

Calculated by through Eviews

Table 3 show that the stationary and non-stationary of the individual variables. The stationary of time series data is compulsory for averting spurious regression analysis because it is impracticable to get good results and making predicting with a non-stationary series. Augmented Dickey-Fuller test showed that some variables are stationary at level and other variables are stationary at 1st difference. This results in indicates that economic growth is integrated at 1st difference and the t-statistic value is-10.73 with 0.00 probability value. The indian tourist and foreign exchange is also stationary at 1st difference. Time series analysis shows that all the variables are integrated at different orders thus there is no co-integration exists among variables and we can use ARDL model

**Table 4: Results of Bound Test**

| Test Statistic | Value | Signif. | I(0) | I(1) |
|---|---|---|---|---|
| F-statistic | 9.09 | 10% | 1.9 | 3.09 |
| k | 4 | 5% | 2.26 | 3.48 |
| | | 1% | 3.07 | 4.44 |

The above table shows the critical values of the upper and lower-bound I(1) and I(0) respectively. The observed F-Statistic value is 9.09 that is greater than the upper-bound of F-Statistics we reject null hypothesis and accept alternative hypothesis, which describes that there is long run association among the variables

**Table 5 Results of long-run relationship between variables**

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| **LnFT** | 0.122 | 0.266 | 0.458 | 0.000 |
| **LnIT** | 0.088 | 0.185 | -0.476 | 0.020 |
| **LnFDI** | 0.190 | 0.145 | 1.307 | 0.030 |
| **LnFE** | 0.130 | 0.679 | 0.191 | 0.050 |

Author's calculation through EViews-10

Table 5 shows the results of ARDL model which indicate that the co-efficient value of foreign tourist in the long run is significant. It reflects positive association with economic growth its means, if one-unit increase in foreign tourist rate the economic growth rate will likely to rise by 0.12 percent. The co-efficient value of indian tourist, foreign direct investment and foreign exchange is statistically significant and positively related to economic growth in the long run. The reason for significant and positive relation in the long run is relative prices and exchange rates represent some of the most critical variables influencing international tourism flows, as they directly affect the affordability of travel. Dwyer, Forsyth, and Rao (2000) emphasize the role of relative price competitiveness, while earlier reviews by Crouch (1994) underscore how exchange-rate changes translate into shifts in demand. Webber (2001) empirically demonstrated that depreciation of a destination's currency often stimulates inbound arrivals, as foreign tourists perceive the destination to be cheaper.

**Table 6: Results of ECM**

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.461 | 0.307 | 8.025 | 0.000 |
| **D(LOGFOREIGN)** | -0.590 | 0.157 | -3.766 | 0.004 |
| **D(LOGFDI)** | 0.609 | 0.128 | 4.741 | 0.001 |
| **CointEq(-1)*** | -0.334 | 0.157 | -8.469 | 0.000 |
| **R-squared** | 0.882 | Mean dependent var | | 0.019 |
| **Adjusted R-squared** | 0.855 | S.D. dependent var | | 0.690 |
| **S.E. of regression** | 0.263 | Akaike info criterion | | 0.368 |
| **Sum squared resid** | 0.898 | Schwarz criterion | | 0.564 |
| **Log likelihood** | 0.872 | Hannan-Quinn criter. | | 0.387 |
| **F-statistic** | 32.450 | Durbin-Watson stat | | 2.109 |
| **Prob(F-statistic)** | 0.000 | | | |

The above table shows that economic growth is the most important variable in the long run and short-run. The value of ECM co-efficient is -0.33 which is negative and significant. This negative and significant coefficient of error correction model indicates the presence of long-run causal relationship. The value of ECM indicates the speed of adjustment from disequilibrium to equilibrium. The value of adjusted $R^2$ is 0.825 which reveals that there is 82.5% variation in economic growth (Dependent variable) due to the change in independent variables. The probability of F-statistic is also statistically significant at 5% level of significance, which justify that the model is goodness of fit.

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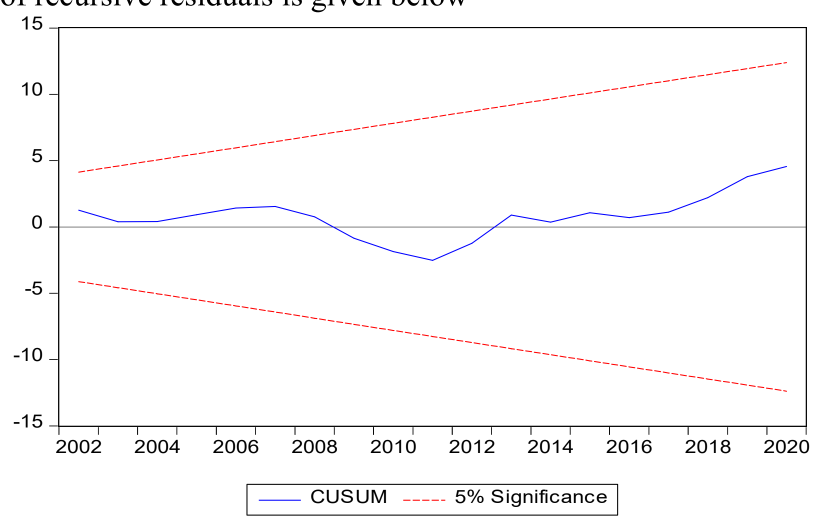
**Table 7, Diagnostic test**

| **Diagnostic test** | F- statistics | P-value |
|---|---|---|
| Breusch-Godfrey Serial Correlation LM Test: | 0.31 | 0.74 |
| Heteroskedasticity Test: Breusch-Pagan-Godfrey | 1.29 | 0.27 |
| Normality test | 0.77 | 0.67 |

Sources; Authors Calculations

Table 7 presents the results of diagnostic tests conducted to identify potential issues in the residuals of the regression model. Specifically, the test checks for serial correlation, that is, whether residuals from one observation are related to those from another. The reported F-statistic is 0.31 with a corresponding p-value of 0.74. Since the p-value is higher than the standard 0.05 threshold, the null hypothesis cannot be rejected, indicating no evidence of serial correlation among the residuals. The test further assesses the homoscedasticity assumption, which refers to the constancy of residual variance across observations. The F-statistic is 1.29 with a p-value of 0.27. As this p-value also exceeds 0.05, the null hypothesis is not rejected, suggesting that the model does not suffer from heteroskedasticity. Additionally, the normality of residuals is examined, which is essential for ensuring valid statistical inference. The test statistic is 0.77 with a p-value of 0.67. Again, since the p-value is greater than 0.05, the null hypothesis is upheld, implying no significant departure from normality. Taken together, the three diagnostic tests confirm that the model satisfies the key assumptions of regression analysis. The absence of serial correlation, heteroskedasticity, and non-normality in the residuals strengthens the credibility and reliability of the study's empirical results.

**Stability of the Model**: Cumulative sum of recursive residuals (CUSUM) tells about the stability of the model with respect to short-run and long-run relationship between variables. The graph of cumulative sum of recursive residuals is given below




Source: Author's calculation through Eviews

CUSUM Test takes the time series on horizontal axis and residual along vertical axis to check the stability of the model. Figure1 shows that CUSUM is within the range 5% critical lines. This critical boundary is not crossed by the graph. So, we can conclude that the model is stable and there is no major gap. This correct specification model accepts the null hypothesis at the 5% significance level.

## 5. Conclusion:

This study examined the key determinants influencing inbound international tourism demand in India through an econometric framework. The findings confirm that both economic and non-economic factors play a significant role in shaping tourist arrivals. Income levels in source countries, relative prices, foreign exchange rates, and transport costs emerged as crucial economic variables, while factors such as safety, infrastructure quality, and policy facilitation (including visa policies) also demonstrated notable influence. The results suggest that higher income in origin countries and competitive price structures tend to boost tourist inflows, whereas higher travel costs and unfavorable exchange rate fluctuations discourage demand. Moreover, institutional and qualitative factors, particularly the image of India as a safe and attractive destination, further strengthen the long-term growth of inbound tourism.

## 6. Suguesstion & Policy Recommendations:

Econometric evidence highlights that income levels in origin countries, relative prices, exchange rates, connectivity, and qualitative factors (safety, image, visa policies) significantly affect inbound tourism demand in India. Thus, India should adopt policies aimed at easing entry, enhancing infrastructure, diversifying attractions, and improving safety and sustainability, while leveraging technology and partnerships to build a resilient and globally competitive tourism sector.

## 7. Study Limitations and Future Work

This study provides important insights into the determinants of inbound international tourism demand in India; however, it is not without limitations. The analysis relies on secondary, aggregate-level data, which restricts the inclusion of qualitative factors such as safety perceptions, cultural appeal, and destination image that significantly influence tourist flows. In addition, short-term shocks such as pandemics, financial crises, or geopolitical tensions are not fully captured, and potential endogeneity among variables may introduce bias in the estimates despite econometric controls. Future research could extend this work by incorporating micro-level or country-specific data to capture heterogeneous tourist preferences, as well as integrating non-economic factors such as infrastructure quality, sustainability practices, and digital platforms in tourism promotion. More dynamic modeling techniques, such as panel cointegration or structural VAR, could be applied to assess both long- and short-term impacts. Moreover, regional and seasonal analyses of inbound tourism within India would provide more granular insights, while future studies should also examine the effects of global shocks, policy initiatives, and sustainable tourism strategies on international demand.

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