

Article

COVID-19 Pandemic Fear and Economic Performance: Empirical Analysis of Tourism and Growth in India

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Abstract

The COVID-19 pandemic generated unprecedented disruptions to the global tourism industry, severely affecting tourism-dependent economies and related employment. India, as one of the world's major tourist destinations, experienced substantial declines in tourist arrivals during the pandemic period. This study investigates the effects of COVID-19-induced fear on tourism demand and economic performance in India using the COVID-19 Fear Index, which captures behavioural responses to pandemic-related uncertainty beyond conventional indicators such as infection rates, mortality, and lockdown restrictions. The COVID-19 Fear Index is constructed using reported COVID-19 cases and mortality data sourced from the European Centre for Disease Prevention and Control and the Johns Hopkins Coronavirus Resource Centre. Monthly data from January 2020 to October 2023 are analysed using autoregressive distributed lag (ARDL) and nonlinear autoregressive distributed lag (NARDL) models to examine both tourism demand dynamics and the asymmetric tourism–growth relationship. The results confirm a stable long-run cointegration relationship among tourism demand, the COVID-19 Fear Index, exchange rate, and ICT development. Pandemic-induced fear significantly reduces tourism demand in the long run (-0.152 , $p = 0.021$) and short run (-0.084 , $p = 0.000$), indicating that heightened uncertainty suppresses tourist arrivals. Exchange rate depreciation also negatively affects tourism demand (-0.267 , $p = 0.000$), whereas ICT development positively enhances tourism resilience (0.463 , $p = 0.000$). The error correction term (-0.436 , $p = 0.000$) confirms rapid adjustment toward long-run equilibrium. Furthermore, the nonlinear analysis reveals asymmetric effects, where positive tourism shocks increase economic growth by 0.088% ($p = 0.003$), while negative shocks exert a stronger contractionary effect (0.409 , $p = 0.000$). These findings highlight the vulnerability of tourism-dependent economies to uncertainty shocks and emphasise the importance of ICT-driven resilience strategies, adaptive tourism policies, and crisis-responsive economic planning.

Keywords: tourism demand; COVID-19 uncertainty; global fear index; asymmetric effects; nonlinear ARDL; tourism–growth nexus; India



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1. Introduction

1.1. Background

Tourism is widely recognised as one of the major drivers of global economic development, contributing significantly to gross domestic product (GDP), employment generation, foreign exchange earnings, and infrastructure development (Singagerda et al., 2023). Prior to the COVID-19 pandemic, the tourism sector contributed approximately 6.9% to India's GDP and supported nearly 8% of total employment, highlighting its strategic importance within the national economy (M. Sharma et al., 2022). Beyond its direct economic contributions, tourism stimulates investment in transportation, hospitality, digital services, and supporting industries, thereby generating broader multiplier effects across the economy (Hajam et al., 2023; Paudel et al., 2024).

Despite its economic importance, tourism remains highly vulnerable to external shocks and uncertainty. Historical crises such as the September 11 terrorist attacks, the SARS outbreak, the global financial crisis, and geopolitical conflicts have demonstrated that disruptive events can substantially reduce tourism flows and revenues (Parray et al., 2023). More recently, the COVID-19 pandemic exposed the structural fragility of global tourism systems and generated one of the most severe disruptions in modern tourism history. In India, the pandemic resulted in the loss of nearly 40 million tourism-related jobs and caused unprecedented declines in tourist arrivals and tourism revenues (Arshad et al., 2021). These developments highlighted the vulnerability of tourism-dependent economies to crisis-induced uncertainty and reinforced the importance of understanding how pandemic-related shocks affect tourism demand and broader macroeconomic performance.

1.2. Tourism Demand, Macroeconomic Uncertainty, and Nonlinear Responses

A growing body of literature suggests that tourism demand is highly sensitive to macroeconomic conditions and uncertainty-related shocks. Exchange rate volatility, inflation, geopolitical risks, economic policy uncertainty, and financial instability significantly influence travel decisions and destination competitiveness (Meo et al., 2018; Munir & Iftikhar, 2021; C. Sharma, 2019). Empirical studies further indicate that tourism responses to uncertainty are frequently nonlinear and asymmetric, where negative shocks generate disproportionately larger effects than positive shocks of comparable magnitude (Parray et al., 2023; C. Sharma & Pal, 2019).

To capture these dynamics, recent tourism studies increasingly employ nonlinear econometric approaches such as the nonlinear autoregressive distributed lag (NARDL) framework (Ghosh, 2020; C. Sharma, 2019). Unlike conventional linear models, the NARDL approach decomposes positive and negative changes separately and allows asymmetric transmission effects to be estimated explicitly. Existing evidence shows that exchange rate movements, geopolitical instability, and uncertainty shocks exert asymmetric effects on tourism demand and economic performance across both developed and emerging economies (Amir et al., 2022; Kisswani et al., 2022; Timur & Mert, 2021).

At the same time, tourism activity itself plays an important role in shaping macroeconomic outcomes. Tourism expansion contributes to employment creation, investment, service sector growth, and foreign exchange earnings, thereby supporting economic growth (Hajam et al., 2023; Paudel et al., 2024). However, recent evidence suggests that downturns in tourism activity may produce stronger macroeconomic contractions than the gains generated during tourism expansions, particularly during crisis periods (Alqaralleh et al., 2025; Mallick et al., 2016; Sekreter et al., 2025). This asymmetric tourism–growth relationship is especially important for emerging economies such as India, where tourism remains closely connected to broader economic development and labour market performance.

1.3. Research Motivation

Although the existing literature provides important insights into tourism demand and the tourism–growth nexus, several important limitations remain. First, many empirical studies continue to rely on conventional linear econometric frameworks that may fail to capture asymmetric adjustments during periods of crisis and uncertainty (Meo et al., 2018; C. Sharma & Pal, 2019). Second, while COVID-19 studies have generally focused on confirmed cases, deaths, lockdown restrictions, or mobility indicators, comparatively limited attention has been given to behavioural and psychological dimensions of uncertainty, particularly COVID-19-induced fear.

Third, relatively few studies integrate tourism demand and economic growth within a unified empirical framework capable of simultaneously examining both symmetric tourism demand responses and asymmetric tourism–growth dynamics. Existing studies also remain geographically concentrated, with limited evidence from major emerging tourism economies such as India during the COVID-19 period. Given the substantial contribution of tourism to employment, foreign exchange earnings, and economic activity in India, understanding the macroeconomic consequences of COVID-19-induced fear remains an important research issue.

1.4. Research Contribution

This study contributes to the tourism and macroeconomic uncertainty literature in several important ways. First, unlike many previous studies that rely on COVID-19 case numbers or mortality indicators, this study employs the COVID-19 Fear Index to capture behavioural and psychological responses associated with pandemic-related uncertainty. This provides a broader understanding of how fear and uncertainty influence tourism activity beyond direct epidemiological effects.

Second, the study incorporates exchange rate and ICT development variables into the tourism demand framework, thereby providing additional insights into the role of macroeconomic conditions and digital connectivity in supporting tourism resilience during crisis periods. Third, the study combines linear autoregressive distributed lag (ARDL) and nonlinear NARDL approaches to jointly examine tourism demand responses and asymmetric tourism–growth dynamics within a unified empirical framework. The ARDL model is appropriate for examining symmetric tourism demand relationships, whereas the NARDL framework is more suitable for identifying hidden asymmetries in the tourism–growth nexus. This integrated modelling structure enables the study to distinguish between symmetric tourism demand effects and asymmetric tourism–growth transmission mechanisms.

Finally, the study contributes new empirical evidence from India, one of the world's major tourism destinations and emerging economies, where limited research currently exists on the relationship between COVID-19-induced fear, tourism demand, and asymmetric economic performance. By employing monthly data from January 2020 to October 2023, the study provides updated evidence on how pandemic-related uncertainty influences tourism activity and broader macroeconomic outcomes.

1.5. Structure of the Paper

The remainder of this paper is organised as follows. Section 2 reviews the relevant literature on tourism demand, macroeconomic uncertainty, and asymmetric tourism–growth relationships. Section 3 presents the empirical model, data, and ARDL/NARDL methodology. Section 4 reports the empirical findings, while Section 5 discusses the broader economic implications of the results. Section 6 presents policy implications, followed by future research directions in Section 7. Finally, Section 8 concludes the study. Figure 1 illustrates the overall research framework and organisation of the study.

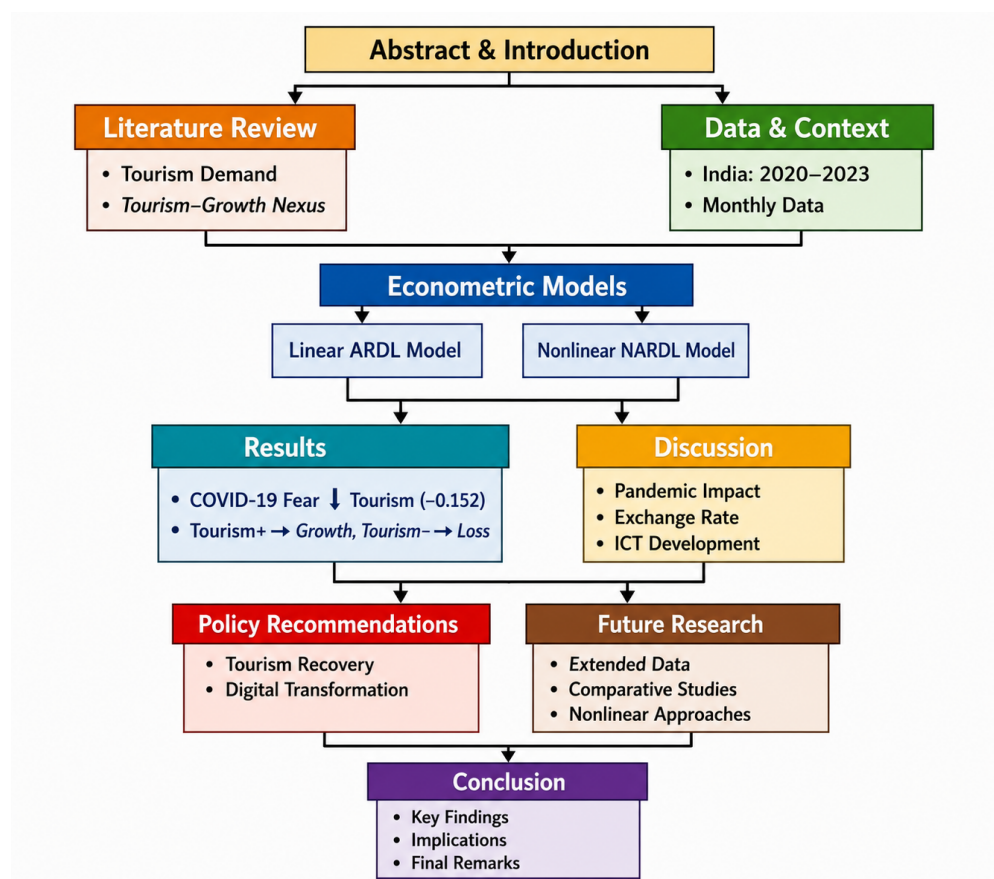


Figure 1. Overall research framework and structure of the study.

2. Literature Review

This section reviews the literature on tourism demand, macroeconomic uncertainty, and the tourism–growth nexus. Section 2.1 examines studies employing linear and symmetric modelling approaches, while Section 2.2 focuses on nonlinear and asymmetric frameworks, particularly NARDL-based studies. Together, these strands provide the theoretical foundation for the ARDL and NARDL models employed in this study.

2.1. Linear Determinants of Tourism Demand

Tourism demand is widely recognised as highly sensitive to macroeconomic conditions and external shocks. A substantial body of literature demonstrates that variables such as exchange rates, inflation, geopolitical risks, and economic activity significantly influence tourism flows and broader tourism performance (Hajam et al., 2023; Paudel et al., 2024; Singh et al., 2025). Tourism development also contributes to economic growth through several transmission channels, including employment generation, foreign exchange earnings, infrastructure development, and increased investment in transportation and hospitality sectors.

Empirical studies frequently employ linear econometric approaches such as autoregressive distributed lag (ARDL), Vector Autoregression (VAR), Vector Error Correction Models (VECMs), and cointegration techniques to investigate both the short-run and long-run relationships between tourism activity and macroeconomic performance (Çınar & Ülker, 2018; Hajam et al., 2023; Paudel et al., 2024). These approaches provide important evidence supporting the tourism-led growth hypothesis and confirm the existence of stable equilibrium relationships between tourism and economic growth.

Studies focusing on India further suggest that macroeconomic conditions, geopolitical risks, and pandemic-related disruptions significantly influence tourism activity and eco-

nomic outcomes (Arshad et al., 2021; Ghosh, 2021). However, most existing studies rely on symmetric econometric frameworks, which assume that positive and negative shocks exert proportional effects on tourism and economic performance.

Table 1 summarises major empirical studies employing linear ARDL and related symmetric modelling approaches to examine tourism demand, tourism growth, and macroeconomic interactions.

2.2. Nonlinear Tourism–Growth Dynamics

Growing evidence suggests that tourism demand and tourism-related economic activity often respond asymmetrically to macroeconomic uncertainty and external shocks. Negative events such as financial crises, geopolitical instability, exchange rate volatility, and pandemic-related uncertainty frequently generate disproportionately larger adverse effects on tourism activity compared with the positive effects associated with favourable economic conditions (Meo et al., 2018; C. Sharma & Pal, 2019).

To capture these nonlinear dynamics, recent studies increasingly adopt nonlinear econometric approaches, particularly the NARDL framework. The NARDL model allows positive and negative changes in explanatory variables to be decomposed and estimated separately, thereby enabling researchers to identify hidden asymmetries in tourism behaviour and economic responses (Ghosh, 2020; C. Sharma, 2019).

Empirical evidence indicates that exchange rate volatility, economic policy uncertainty, geopolitical risks, environmental degradation, and tourism shocks exert asymmetric effects on tourism demand and economic growth across different economies (Amir et al., 2022; Munir & Iftikhar, 2021; Parray et al., 2023). More recent studies also show that negative tourism shocks often generate stronger macroeconomic contractions than the gains associated with positive tourism expansions (Alqaralleh et al., 2025; Sekreter et al., 2025).

Table 2 summarises empirical studies employing nonlinear ARDL and related asymmetric modelling approaches in tourism economics.

2.3. Conceptual Framework and Hypotheses

The relationships among COVID-19-induced fear, tourism demand, and economic growth are illustrated in Figure 2. The conceptual framework demonstrates how pandemic-induced uncertainty, together with exchange rate movements and ICT development, influences tourism demand in India. In turn, changes in tourism activity affect broader economic performance through both positive and negative tourism shocks. The framework therefore integrates the tourism demand model and the tourism–growth nexus within a unified empirical structure and provides the theoretical foundation for the ARDL and NARDL specifications employed in this study. Specifically, the tourism demand model is examined using a linear ARDL framework to estimate symmetric effects, while the tourism–growth nexus is analysed using a nonlinear ARDL (NARDL) framework to capture asymmetric responses.

Specifically, the framework assumes that heightened COVID-19-induced fear increases uncertainty and perceived travel risk, thereby reducing international tourism demand. Exchange rate fluctuations further influence tourism competitiveness and travel affordability, while ICT development enhances tourism resilience through digital connectivity, online services, and information accessibility. At the macroeconomic level, changes in tourism activity subsequently influence economic growth through employment generation, foreign exchange earnings, investment, and service sector expansion. However, these tourism effects may not be symmetric, as negative tourism shocks during crisis periods can generate disproportionately larger economic contractions than the gains associated with tourism recovery and expansion.

Table 1. Empirical studies using linear ARDL and symmetric tourism models.

Study	Methodology	Period	Key Findings	Strengths	Limitations	Challenges/Notes
(Ghosh, 2021)	Bayer–Hanck cointegration, ARDL, VECM	Unspecified	Geopolitical risk adversely affects inbound tourism in India.	Robust evidence with macroeconomic controls.	Linear framework only; no asymmetric modelling.	Small-sample cointegration issues.
(Arshad et al., 2021)	Time series modelling	2020	COVID-19 severely affected Indian tourism GDP and employment.	Quantifies early pandemic-related tourism losses.	Descriptive framework without econometric asymmetry analysis.	Data scarcity during lockdown periods.
(Singh et al., 2025)	ARDL bounds testing	Unspecified	Macroeconomic determinants significantly influence tourist arrivals in India.	Applies specific-to-general modelling framework.	Assumes symmetric relationships.	Mixed integration orders across variables.
(Paudel et al., 2024)	VAR	Unspecified	Tourism, economic growth, and CO ₂ emissions exhibit causal interrelationships in South Asia.	Employs a multivariate dynamic framework.	Symmetric framework may overlook nonlinear responses.	Sensitive to stationarity conditions.
(Hajam et al., 2023)	ARDL	1990–2018	Tourism receipts and expenditures positively affect economic growth in India.	Provides evidence supporting the tourism-led growth hypothesis.	Aggregate linear framework only.	Lack of sectoral disaggregation.
(Çınar & Ülker, 2018)	ARDL, cointegration	Unspecified	Long-run tourism–growth relationships exist across economies.	Comprehensive tourism–growth nexus analysis.	Region-specific findings limit broader generalisation.	Country-specific structural characteristics.
(Selvanathan et al., 2020)	ARDL, VECM, panel analysis	1990–2014	Tourism contributes to GDP, energy consumption, and CO ₂ emissions in South Asia.	Captures dynamic interrelationships among tourism, economy, and environment.	Symmetric modelling framework only.	Sensitivity to global economic conditions.

Table 2. Empirical studies on NARDL and asymmetric tourism effects.

Study	Methodology	Period	Key Findings	Strengths	Limitations	Challenges/Notes
(C. Sharma & Pal, 2019)	Nonlinear ARDL	2006M1–2018M4	Exchange rate volatility exerts asymmetric effects on tourism demand, with stronger long-run negative effects.	First NARDL application in Indian tourism demand literature capturing nonlinearities.	Pre-COVID-19 framework; excludes uncertainty and growth nexus variables.	Monthly data limits broader crisis interpretation.
(C. Sharma, 2019)	NARDL	2006M1–2018M4	Economic policy uncertainty asymmetrically affects tourism demand in India.	Confirms nonlinear uncertainty effects on tourism activity.	Pre-COVID-19 and India-specific focus only.	Measuring policy uncertainty in emerging economies.
(Meo et al., 2018)	NARDL	Unspecified	Oil prices, exchange rates, and inflation generate asymmetric long-run tourism effects.	Demonstrates importance of nonlinear macroeconomic effects.	Pakistan-specific study without COVID-19 context.	Potential small-sample bias.

Table 2. Cont.

Study	Methodology	Period	Key Findings	Strengths	Limitations	Challenges/Notes
(Munir & Iftikhar, 2021)	Panel linear & NARDL	1995–2019	Exchange rate and FDI shocks asymmetrically influence tourism activity in South Asia.	Provides regional evidence on tourism asymmetries.	Regional aggregation masks country-specific effects.	Cross-country policy heterogeneity.
(Ghosh, 2020)	NARDL	1996Q1–2020Q1	COVID-19 uncertainty asymmetrically reduces Chinese tourist arrivals.	Novel pandemic uncertainty index application.	Limited to Australia–China tourism flows.	Early-pandemic data volatility.
(Parra et al., 2023)	NARDL	2001Q1–2019Q4	Geopolitical risk shocks exert asymmetric effects on tourism demand.	Captures hidden asymmetries beyond linear models.	Pre-COVID-19 setting without broader macroeconomic controls.	Volatility in geopolitical risk indicators.
(Amir et al., 2022)	NARDL, Granger Causality	1995–2019	Environmental degradation, economic growth, exchange rates, and inflation exert asymmetric effects on tourism demand in Pakistan.	Integrates environmental and macroeconomic determinants within a nonlinear tourism demand framework and identifies both long-run asymmetries and causal relationships.	Limited to Pakistan and does not consider pandemic-related uncertainty, behavioural responses, or crisis-induced fear.	Ensuring stationarity, nonlinear cointegration, and interpretation of asymmetric responses across multiple macroeconomic variables.
(Khan et al., 2021)	NARDL	Unspecified	Tourism–growth relationship exhibits asymmetric dynamics in Bangladesh.	Applies nonlinear framework under crisis conditions.	Bangladesh-specific findings.	Small sample limitations.
(Rej et al., 2025)	NARDL, frequency causality	1980–2017	Terrorism and military expenditure asymmetrically affect Indian tourism demand.	Provides security-related asymmetry evidence for India.	Excludes pandemic-related uncertainty.	Structural breaks over long sample periods.
(Alqaralleh et al., 2025)	Panel Quantile ARDL	Unspecified	Tourism–growth relationship varies asymmetrically across regions and development levels.	Quantile framework captures heterogeneous responses.	No India-specific or COVID-related analysis.	Heterogeneous panel integration issues.
(Sekreter et al., 2025)	Hatemi-J asymmetric causality, hidden cointegration	1990–2023	Tourism receipts exert asymmetric causal effects on economic growth.	Highlights tourism resilience during downturns.	Turkey-specific framework.	Interpretation of asymmetric causality.
(Kiswani et al., 2022)	NARDL, Toda–Yamamoto causality	1995–2019	Exchange rate movements asymmetrically affect tourism inflows in ASEAN-5 economies.	Captures exchange rate asymmetries with structural breaks.	ASEAN-focused analysis only.	Diverse causality directions across countries.
(Timur & Mert, 2021)	NARDL	2003Q1–2020Q1	Exchange rate movements generate asymmetric long-run tourism revenue effects in Turkey.	Demonstrates nonlinear exchange rate transmission effects.	Turkey-specific findings.	Long-run asymmetry with short-run symmetry.

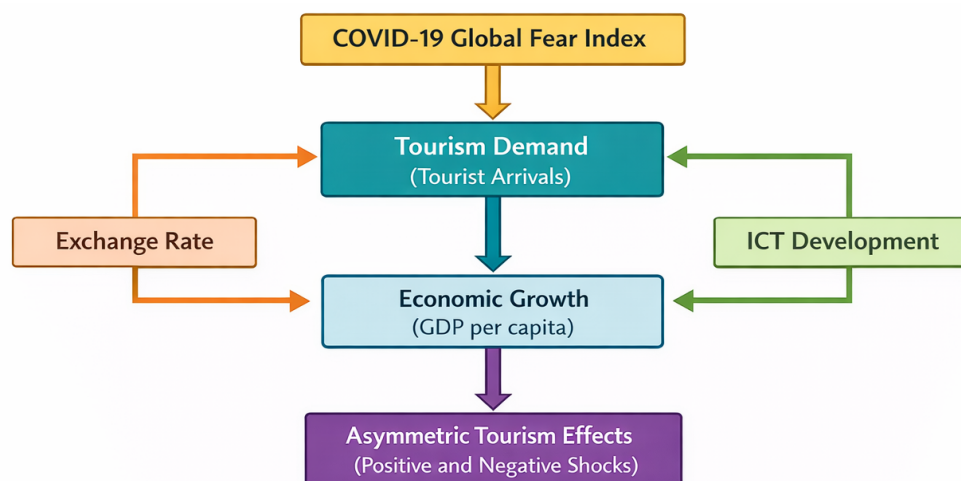


Figure 2. Conceptual framework of the study linking COVID-19-induced fear, exchange rate, ICT development, tourism demand, and economic growth.

Figure 2 summarises the theoretical relationships examined in the empirical analysis.

Based on the theoretical and empirical literature discussed above, the study proposes the following hypotheses:

H1. *The COVID-19-induced fear index negatively affects tourism demand in India.*

H2. *Positive and negative tourism shocks exert asymmetric effects on economic growth in India.*

3. Empirical Model and Data

This study employs two complementary econometric frameworks. First, a linear ARDL model is estimated to examine the symmetric effects of COVID-19-induced fear, exchange rate, and ICT development on tourism demand. Second, a nonlinear ARDL (NARDL) model is employed to investigate whether positive and negative tourism shocks exert asymmetric effects on economic growth.

Following the literature on crisis-induced uncertainty and its adverse effects on tourism demand—particularly amid COVID-19 disruptions that halted travel, threatened GDP contributions (6.9% in India), and amplified economic fears (Arshad et al., 2021; Ghosh, 2020, 2021)—we formulate a baseline bivariate model treating the global fear index (GFI) as the primary predictor to isolate its direct impact. This approach aligns with studies employing time series models for India and South Asia to capture short- and long-run dynamics robust to non-stationarities and shocks (Hajam et al., 2023; Paudel et al., 2024; Selvanathan et al., 2020; Singh et al., 2025).

Given the time series data, we estimate the following long-run relationship:

$$\ln Tur_t = \alpha_0 + \alpha_1 \ln COV19_t + \varepsilon_t \quad (1)$$

The variables are characterised by a unit root process, where $\ln Tur_t$ is the log of the tourism arrival series, $\ln COV19_t$ is the log of the COVID-19 GFI series, α_0 is a constant parameter, and ε_t is a white noise error term. The underlying theoretical relationship posits that heightened COVID-19-induced fear reduces global economic activity, thereby curtailing travel and tourism arrivals (Arshad et al., 2021; Ghosh, 2020).

We further extend the bivariate model to examine how other economic fundamentals influence tourism during the crisis:

$$\ln Tur_t = \alpha_0 + \alpha_1 \ln COV19_t + \gamma_1 \ln EXR_t + \gamma_2 \ln ICT_t + \varepsilon_t \quad (2)$$

where $\ln EXR_t$ is the log nominal exchange rate and $\ln ICT_t$ is the log ICT series, with γ as the vector of parameters for these controls. Exchange rate appreciation reduces tourists' purchasing power, negatively affecting arrivals (Amir et al., 2022; Jackman et al., 1980; Kiswani et al., 2022; Timur & Mert, 2021). ICT development supports tourism infrastructure and digital promotion, enhancing resilience.

We use monthly observations from January 2020 to October 2023. Data on international tourist arrivals, exchange rate and ICT (proxied by mobile phone subscription) are obtained from World Development Indicators (WDI).

ICT development was included because digital connectivity and online information access became increasingly important for tourism-related activities during the COVID-19 period, including travel planning, digital services, and communication. In the Indian context, ICT infrastructure also plays a significant role in supporting tourism recovery and economic resilience.

The exchange rate variable was incorporated because currency fluctuations influence the relative cost of travel and tourism competitiveness. In India, exchange rate movements can affect international tourism inflows by altering travel affordability for foreign tourists.

The GFI was constructed following (Salisu & Akanni, 2020). The GFI attempts to measure risk emanating from the spread of COVID-19. GFI is a composite index of two other indexes: (i) the reported cases index; and (ii) the reported death index (RDI). The detailed derivation and construction procedure of the GFI are provided in Appendix A. These indices are on a scale of 0–100, indicating low and high risk caused by COVID-19.

The data for reported cases and deaths are obtained from the European Centre for Disease Prevention and Control and Johns Hopkins Coronavirus Resource Centre.

The COVID-19 Fear Index was selected because the study aims to capture the psychological and uncertainty effects of the pandemic on tourism arrivals rather than only the direct health impacts measured by COVID-19 cases or deaths. The fear index better reflects travelers' behavioural responses and risk perceptions.

Econometric Methodology

The baseline bivariate model and its extension specified in Section 3 are estimated for India using Pesaran et al. (2001)'s ARDL procedure, which is suitable for variables of mixed integration orders and small samples (Hajam et al., 2023; Singh et al., 2025). The dynamic ARDL in its general form is:

$$\begin{aligned} \Delta \ln Tur_t = & \alpha_0 + \sum_{i=1}^p \alpha_{1i} \Delta \ln Tur_{t-i} + \sum_{i=0}^q \alpha_{2i} \Delta \ln COV19_{t-i} \\ & + \sum_{i=0}^r \alpha_{3i} \Delta Z_{t-i} + \theta_1 \ln Tur_{t-1} + \theta_2 \ln COV19_{t-1} + \theta_3 Z_{t-1} + \varepsilon_t, \end{aligned} \quad (3)$$

where $Z_t = [\ln EXR_t, \ln ICT_t]^\top$ denotes the control variables (Amir et al., 2022; Kiswani et al., 2022; Timur & Mert, 2021). This unrestricted error correction model facilitates bounds testing for cointegration (Hajam et al., 2023; Singh et al., 2025).

If cointegration is confirmed, the short-run dynamics are derived from the ECM:

$$\begin{aligned}\Delta \ln Tur_t = & \beta_0 + \sum_{i=1}^p \beta_{1i} \Delta \ln Tur_{t-i} + \sum_{i=0}^q \beta_{2i} \Delta \ln COV19_{t-i} \\ & + \sum_{i=0}^r \beta_{3i} \Delta Z_{t-i} + \lambda \widehat{ECM}_{t-1} + \varepsilon_t,\end{aligned}\quad (4)$$

where $\lambda < 0$ and $|\lambda| < 1$ signifies the speed of adjustment to long-run equilibrium (Ojaghlou, 2019; Selvanathan et al., 2020). Prior to estimation, Phillips–Perron unit root tests confirm the integration properties, ensuring ARDL applicability.

We also examine the impact of the COVID-19 pandemic and tourism on India's economic growth ($\ln y_t$, real per capita GDP).

The main independent variable (COV19) used in this study is available only on a monthly basis. To maintain consistency, annual GDP was converted into a monthly frequency using the cubic interpolation method. This approach is commonly used in empirical research when higher-frequency macroeconomic series are required, but only lower-frequency official data are available.

We employ the nonlinear ARDL model of Shin et al. (2014) due to the asymmetric nature of COVID-19 as a negative shock and tourism-led growth dynamics (Brida et al., 2016; Ghosh, 2020; Khan et al., 2021; Ojaghlou, 2019; Parray et al., 2023).

Unlike the linear ARDL specification, which assumes symmetric adjustment, the NARDL framework allows positive and negative tourism shocks to affect economic growth differently. NARDL extends ARDL by decomposing tourism into positive (Tur_t^+) and negative (Tur_t^-) partial sums, capturing asymmetries unobserved in linear models (Amir et al., 2022; Kiswani et al., 2022; Timur & Mert, 2021).

The NARDL($p, q_1, q_2, q_3, q_4^+, q_4^-$) specification is:

$$\begin{aligned}\Delta \ln y_t = & \alpha_0 + \alpha_1 \ln y_{t-1} + \alpha_2 \ln COV19_{t-1} + \alpha_3 \ln ICT_{t-1} + \alpha_4^+ Tur_{t-1}^+ + \alpha_4^- Tur_{t-1}^- \\ & + \sum_{i=1}^p \beta_{1i} \Delta \ln y_{t-i} + \sum_{i=0}^{q_1} \beta_{2i} \Delta \ln COV19_{t-i} + \sum_{i=0}^{q_2} \beta_{3i} \Delta \ln ICT_{t-i} \\ & + \sum_{i=0}^{q_3} \beta_{4i}^+ \Delta Tur_{t-i}^+ + \sum_{i=0}^{q_4} \beta_{4i}^- \Delta Tur_{t-i}^- + \varepsilon_t,\end{aligned}\quad (5)$$

where

$$Tur_t^+ = \sum_{j=1}^t \max(\Delta \ln Tur_j, 0), \quad Tur_t^- = \sum_{j=1}^t \min(\Delta \ln Tur_j, 0), \quad (6)$$

such that

$$\ln Tur_t = \ln Tur_0 + Tur_t^+ + Tur_t^-. \quad (7)$$

Long-run asymmetries are tested via Wald restrictions, and the ECM form is:

$$\begin{aligned}\Delta \ln y_t = & \rho \varsigma_{t-1} + \sum_{i=1}^p \beta_{1i} \Delta \ln y_{t-i} + \sum_{i=0}^{q_1} \beta_{2i} \Delta \ln COV19_{t-i} \\ & + \sum_{i=0}^{q_2} \beta_{3i} \Delta \ln ICT_{t-i} + \sum_{i=0}^{q_3} \beta_{4i}^+ \Delta Tur_{t-i}^+ \\ & + \sum_{i=0}^{q_4} \beta_{4i}^- \Delta Tur_{t-i}^- + \varepsilon_t,\end{aligned}\quad (8)$$

where ς_{t-1} embeds the asymmetric long-run equilibrium and $\rho < 0$ denotes the adjustment speed (Khan et al., 2021; Parray et al., 2023). Bounds F-tests confirm cointegration, with the Schwarz criterion used for lag selection.

4. Results

This section presents the empirical findings of the study in a structured manner. It first reports the time series properties of the variables, followed by the linear ARDL estimates for tourism demand and the nonlinear ARDL estimates for the tourism–growth relationship.

4.1. Unit Root Tests

Prior to estimating the ARDL and NARDL models, the stationarity properties of the variables are examined using the Phillips–Perron (PP) unit root test. The PP approach is appropriate in this context because it is robust to serial correlation and heteroskedasticity in the residuals without requiring explicit modelling of these features (Ghosh, 2020; Singh et al., 2025). The test is performed for each variable in both level and first-difference form, under specifications with and without a deterministic trend.

The results reported in Table 3 indicate that all variables— $\ln y_t$, $\ln \text{COV19}_t$, $\ln \text{Tur}_t$, $\ln \text{ICT}_t$, and $\ln \text{EXR}_t$ —are non-stationary in levels but become stationary after first differencing. Specifically, the first-difference PP statistics are significant across both trend specifications, confirming that each series is integrated of order one, $I(1)$. This outcome satisfies the precondition for applying the ARDL bounds testing framework and supports the subsequent use of both linear and nonlinear cointegration models.

Table 3. Phillips–Perron unit root test results.

Variables	No Trend		Trend	
	Level	1st Diff	Level	1st Diff
ly	−1.950	−4.293 *	−0.669	−6.687 *
$l\text{COV19}$	−0.663	−4.169 *	−0.663	−4.116 **
$l\text{Tour}$	−0.946	−7.536 *	−2.120	−7.451 *
$l\text{ICT}$	−0.094	−2.863 ***	−1.979	−9.011 *
$l\text{EXR}$	−1.093	−4.234 *	−1.224	−4.373 *

Notes: The numbers reported are the test statistics. The null hypothesis indicates that the series contains a unit root for which MacKinnon p -values are used. *, ** and *** imply significance at 1%, 5% and 10%, respectively.

4.2. Linear ARDL Results: Tourism and COVID-19

Having established the integration order of the variables, the next step is to estimate the linear ARDL model for tourism demand, where tourism arrivals ($\ln \text{Tur}_t$) are modelled as a function of the COVID-19 GFI, exchange rate, and ICT development. Optimal lag length is selected using the Schwarz information criterion (Singh et al., 2025). The first stage of the ARDL procedure is the bounds test for cointegration.

As shown in Table 4, the computed F-statistic of 9.02 exceeds the upper critical bound of 5.07 at the 1% significance level. This confirms the existence of a stable long-run cointegrating relationship among $\ln \text{Tur}_t$, $\ln \text{COV19}_t$, $\ln \text{ICT}_t$, and $\ln \text{EXR}_t$. Hence, the long-run and short-run ARDL estimates are statistically meaningful and can be interpreted as evidence of equilibrium linkages between pandemic uncertainty and tourism activity.

The long-run estimates indicate that the COVID-19-induced fear index exerts a statistically significant negative effect on tourism arrivals, with a coefficient of -0.152 ($p = 0.021$). This implies that a 1% increase in pandemic-induced fear reduces tourist arrivals by approximately 0.152%.

Table 4. Effect of COVID-19 on tourism.

Panel A (a): Long Run				(b): Short Run			
Variable	Coefficient	SE	p-Value	Variable	Coefficient	SE	p-Value
<i>ICOV19</i>	−0.152 **	0.063	0.021	Δ <i>ICOV19</i>	−0.084 *	0.018	0.000
<i>IEXR</i>	−0.267 *	0.059	0.000	Δ <i>IEXR</i>	−0.171 *	0.041	0.000
<i>IICT</i>	0.463 *	0.047	0.000	Δ <i>IICT</i>	0.329 *	0.116	0.001
Constant	1.226 *	0.015	0.000	Constant	−0.979 *	0.053	0.000
Trend	0.016	0.015	0.284	Trend	0.052 **	0.026	0.056
<i>ECM</i> _{<i>t</i>−1}					−0.436 *	0.001	0.000
Panel B: Model diagnostic test							
Serial correlation: (1) = 1.688 (0.158)				<i>R</i> ² = 0.635			
Functional form: (1) = 0.978 (0.717)				Adjusted <i>R</i> ² = 0.617			
Normality: (2) = 5.268 (0.230)				DW-statistic = 2.431			
Heteroscedasticity: (1) = 1.436 (0.213)				SE of regression = 0.006			
Panel C: F-test							
F-statistic: 9.02 *							
Lower bound				Upper bound			
1%: 3.89				1%: 5.07			
5%: 3.47				5%: 4.57			
10%: 3.03				10%: 4.06			

Notes: * and ** indicate significance at the 1% and 5% levels, respectively. SE is the standard error and DW is the Durbin–Watson statistic for autocorrelation. The probability value for the model diagnostic test is in parentheses. Critical bounds values are from (Narayan & Narayan, 2005).

The negative coefficient indicates that heightened COVID-19-induced fear and uncertainty significantly reduced tourism demand by increasing perceived travel risks and discouraging mobility. Unlike conventional pandemic indicators such as infection cases or mortality rates, the fear index captures behavioural responses and risk perceptions associated with uncertainty. In India, lockdown measures, travel restrictions, and widespread media coverage likely intensified fear-related responses and contributed to declining tourism inflows.

The exchange rate also carries a negative long-run coefficient of -0.267 ($p = 0.000$), suggesting that currency depreciation is associated with weaker international tourism inflows.

Currency instability may reduce tourism demand by increasing travel uncertainty and affecting travel affordability. Although currency depreciation can sometimes improve tourism competitiveness by making destinations cheaper for foreign tourists, excessive exchange rate volatility during periods of economic uncertainty may discourage international travel decisions. In the Indian context, fluctuations in the exchange rate during the pandemic period were associated with broader macroeconomic instability, reduced global economic activity, and weaker international travel confidence, all of which contributed to lower tourism inflows.

Conversely, ICT development has a positive long-run elasticity of 0.463 ($p = 0.000$), indicating that digital readiness and communication infrastructure support tourism demand even under crisis conditions.

The positive ICT coefficient suggests that digital infrastructure enhanced tourism resilience during the pandemic period by improving access to online services, digital payment systems, tourism information, and communication platforms. In the Indian context, expanding internet penetration and digital tourism services likely strengthened tourism accessibility and supported recovery under conditions of heightened uncertainty.

The short-run dynamics reinforce these findings. The coefficient on $\Delta/COV19$ is -0.084 ($p = 0.000$), confirming that increases in COVID-19-induced fear immediately depress tourism demand.

Likewise, exchange rate changes continue to have a significant short-run negative effect on international tourism (-0.171 , $p = 0.000$), while ICT remains positive and statistically significant (0.329 , $p = 0.010$).

The error correction coefficient, $ECM_{t-1} = -0.436$ ($p = 0.000$), is negative and highly significant, indicating that approximately 44% of deviations from the long-run equilibrium are corrected within one period. This relatively high speed of adjustment suggests a strong tendency for the tourism system to revert to equilibrium after shocks.

The diagnostic statistics also support the adequacy of the estimated ARDL model. The absence of serial correlation, functional form misspecification, heteroscedasticity, and non-normality indicates that the model is econometrically well behaved. The explanatory power is also reasonably strong, with $R^2 = 0.635$ and an adjusted $R^2 = 0.617$.

4.3. Nonlinear ARDL Results: Tourism, COVID-19, and Economic Growth

While the ARDL model estimates symmetric tourism demand responses, the NARDL framework evaluates whether positive and negative tourism shocks generate asymmetric effects on economic growth. To examine whether tourism shocks exert asymmetric effects on economic performance, the study next estimates a nonlinear ARDL model in which real per capita GDP is modelled as a function of positive and negative tourism shocks, COVID-19-induced fear, ICT development, and capital stock. This specification is appropriate because pandemic disruptions and tourism contractions may affect output more strongly than tourism expansions of similar magnitude (Ghosh, 2020; Kisswani et al., 2022).

The bounds test again supports the presence of a stable long-run relationship. As shown in Table 5, the F-statistic of 5.13 exceeds the upper critical bound of 5.07 at the 1% level, confirming nonlinear cointegration among $\ln GDP_{pc,t}$, $\ln Tur_t$, $\ln COV19_t$, $\ln ICT_t$, and $\ln K_t$. In addition, the Wald tests reject the null hypothesis of symmetry in both the long run and short run, thereby validating the use of the NARDL framework and confirming the presence of asymmetric tourism effects in India.

The long-run coefficients reveal a marked asymmetry in the tourism–growth nexus. Positive tourism shocks increase real per capita GDP by 0.088% for each 1% rise in tourism ($p = 0.003$). Conversely, negative tourism shocks are associated with a coefficient of 0.409 ($p = 0.000$) in absolute magnitude, indicating that adverse tourism movements have a much stronger macroeconomic impact than favourable tourism expansions.

The findings suggest that positive and negative changes in tourism arrivals do not affect economic growth in the same manner. Positive tourism shocks may stimulate economic activity through increased employment, foreign exchange earnings, investment, and service sector expansion. However, negative tourism shocks—such as those experienced during the COVID-19 pandemic—may produce disproportionately larger adverse effects on economic growth due to reduced business activity, lower income generation, and declines in tourism-related services. This asymmetry indicates that economic growth in India may be more vulnerable to tourism downturns than it benefits from tourism expansions, emphasising the importance of developing resilient tourism and crisis management policies.

COVID-19-induced fear exerts a negative long-run effect on growth (-0.316 , $p = 0.072$).

This implies that beyond the direct health effects of COVID-19, fear suppresses economic activity. The negative coefficient reflects the contractionary effects of uncertainty on economic activity. At the time of extreme uncertainty, households cut down on travel, consumption and recreation, while businesses delay investment. Given that tourism is highly reliant on consumer confidence, fear severely weakens tourism demand and related economic activities.

Table 5. Nonlinear ARDL estimation.

Panel A (a): Long Run				(b): Short Run			
Variable	Coefficient	SE	p-Value	Variable	Coefficient	SE	p-Value
IK_t	0.560 *	0.068	0.000	ΔIK_t	0.472 *	0.141	0.003
$ITur_t^+$	0.088 *	0.024	0.003	$\Delta ITur_t^+$	0.071 *	0.016	0.000
$ITur_t^-$	0.409 *	0.063	0.000	$\Delta ITur_t^-$	0.095 *	0.025	0.002
$ICOV19$	-0.316 ***	0.162	0.072	$\Delta ICOV19$	-0.278 *	0.069	0.001
$IICT$	0.044 *	0.016	0.011	$\Delta IICT$	0.022 *	0.006	0.005
Constant	1.076 **	0.447	0.031	Constant	1.033 *	0.071	0.000
Trend	0.053	0.270	0.845	Trend	0.106	0.078	0.183
ECM_{t-1}					-0.682 *	0.100	0.000
Panel B: Model diagnostic test							
Serial correlation: (1) = 0.317 (0.732)				$R^2 = 0.806$			
Functional form: (1) = 1.252 (0.277)				Adjusted $R^2 = 0.754$			
Normality: (2) = 1.467 (0.480)				DW-statistic = 2.282			
Heteroscedasticity: (1) = 0.621 (0.817)				SE of regression = 0.003			
Panel C: F-test							
F-statistic: 5.13 *							
Lower bound		Upper bound					
1%: 3.89		1%: 5.07					
5%: 3.47		5%: 4.57					
10%: 3.03		10%: 4.06					
Panel D: Asymmetric test							
Null hypothesis: Tourism has a symmetric effect on real per capita GDP							
Long run: (1) = 2.615 (0.021) **				Short run: (1) = 5.045 (0.024) **			

Notes: *, ** and *** indicate significance at the 1%, 5% and 10% levels, respectively. SE is the standard error and DW is the Durbin–Watson statistic for autocorrelation. The probability value for the model diagnostic test is in parentheses. Critical bounds values are from (Narayan & Narayan, 2005).

ICT is positive and statistically significant, with a coefficient of 0.044 ($p = 0.011$).

The positive ICT coefficient indicates that digital transformation enhances service efficiency, tourism accessibility, and economic adaptability. ICT infrastructure supports tourism-related services such as online booking, digital payments, marketing, and information dissemination, thereby strengthening tourism competitiveness and broader economic performance.

Capital stock also remains strongly growth-enhancing, with a long-run elasticity of 0.560 ($p = 0.000$).

This finding is consistent with economic growth theory, where investment enhances productive capacity, infrastructure development, and long-run economic performance. In the tourism sector, investment in transportation, hospitality infrastructure, and connectivity further strengthens tourism-led growth channels.

The short-run dynamics are broadly consistent with the long-run results. Positive tourism shocks remain growth-enhancing (0.071, $p = 0.000$), while negative shocks are again significant (0.095, $p = 0.002$), reinforcing the asymmetric adjustment pattern. The short-run coefficient on COVID-19-induced fear is negative and statistically significant (−0.278, $p = 0.001$), indicating that pandemic-related uncertainty also exerts immediate output costs. ICT and capital stock continue to support growth in the short run, with coefficients of 0.022 ($p = 0.005$) and 0.472 ($p = 0.003$), respectively.

The error correction term is negative and highly significant (−0.682, $p = 0.000$), implying that around 68% of short-run disequilibria are corrected within one period. Compared with the linear ARDL model, this faster speed of adjustment suggests that the tourism–growth system converges more rapidly towards its long-run equilibrium when asymmetric effects are explicitly incorporated. Diagnostic tests confirm that the estimated

model is robust, with no evidence of serial correlation, functional form misspecification, heteroscedasticity, or non-normality. The model also demonstrates adequate explanatory power, with $R^2 = 0.806$ and an adjusted $R^2 = 0.754$.

5. Discussion

5.1. Symmetric Tourism Demand Effects

The results provide strong evidence that tourism demand in India is highly sensitive to uncertainty shocks generated by the COVID-19 pandemic. The negative long-run elasticity of -0.152 and the short-run coefficient of -0.08 indicate that COVID-19-induced fear substantially reduced tourist arrivals, both immediately and persistently. This pattern is consistent with the argument that crisis-induced uncertainty alters travel behaviour by raising perceived risk, discouraging discretionary mobility, and reducing the willingness of households to commit expenditure to tourism-related consumption (Ghosh, 2020). In this sense, the tourism market appears to respond not only to objective restrictions but also to subjective perceptions of risk.

The exchange rate results add a further macroeconomic dimension to the tourism shock. The negative coefficients of -0.267 in the long run and -0.171 in the short run suggest that exchange rate depreciation did not improve tourism competitiveness during the pandemic period. Rather, it likely signalled broader economic instability and reduced confidence in destination conditions, consistent with asymmetric exchange rate evidence reported in earlier tourism studies (Kisswani et al., 2022; Timur & Mert, 2021). This is an important finding because it implies that conventional competitiveness channels may weaken or even reverse during crisis episodes.

Conversely, ICT development emerges as a statistically significant resilience factor. The estimated ICT coefficients are consistently positive across both the tourism demand and growth equations. In the tourism model, ICT coefficients of 0.463 in the long run and 0.329 in the short run suggest that digital infrastructure, online booking systems, digital communication, and information accessibility helped partially offset the disruptive effects of the pandemic.

In the growth model, ICT also supports output, with long-run and short-run coefficients of 0.044 and 0.022 , respectively. These findings imply that digital preparedness functions as both a tourism support mechanism and a broader productivity-enhancing channel.

5.2. Asymmetric Tourism–Growth Effects

The nonlinear results are particularly important from a theoretical and policy perspective. The Wald statistics reject symmetry in both the long run and short run, confirming that positive and negative tourism shocks do not affect growth equally. This aligns with the growing literature showing that tourism-led growth is not mechanically linear, especially in shock-prone economies (Alqaralleh et al., 2025; Khan et al., 2021). The estimated asymmetry suggests that declines in tourism generate disproportionately large macroeconomic costs relative to the gains produced by tourism expansion.

This asymmetry is consistent with the structural characteristics of tourism-dependent economies because tourism downturns tend to transmit rapidly through labour markets, transport services, hospitality networks, informal employment, and foreign exchange earnings. Once these linkages are disrupted, recovery is often slower and more uneven than the initial contraction.

The error correction terms provide additional insight into system adjustment. The tourism demand model corrects approximately 44% of short-run disequilibrium within one period, whereas the nonlinear growth model corrects approximately 68% within the same period. This indicates that both systems converge toward their long-run equilibrium,

with the tourism–growth model exhibiting a relatively faster speed of adjustment. The results suggest that economic growth responds strongly to changes in tourism activity and adjusts rapidly following short-run disturbances. Nevertheless, tourism recovery does not automatically translate into immediate macroeconomic normalisation, as broader sectoral and structural effects may persist beyond the initial adjustment process.

Taken together, the empirical evidence confirms that pandemic-related uncertainty is not merely a temporary disturbance to tourism flows; it has broader structural consequences for macroeconomic performance in tourism-linked economies. The results therefore support the view that tourism resilience should be understood not only as a sectoral concern but as an integral component of wider economic stability and crisis preparedness (Hajam et al., 2023; Selvanathan et al., 2020).

6. Policy Implications

The findings of this study carry several important policy implications for India and other tourism-dependent emerging economies. First, the strongly negative COVID-19-induced fear coefficients suggest that governments must treat risk communication and crisis management as core components of tourism policy. Since a 1% increase in pandemic fear reduces tourism arrivals by approximately 0.15% in the long run, policy responses should not be limited to border reopening alone. Clear public communication, health security protocols, real-time destination information, and credible emergency governance are essential to restoring traveller confidence during and after crisis periods.

Second, the positive role of ICT implies that digital transformation should be positioned at the centre of tourism resilience strategies. Investments in digital booking ecosystems, contactless travel services, smart destination management, integrated tourism information systems, and platform-based SME participation can strengthen the adaptability of the tourism sector. The significance of ICT in both the tourism and growth equations indicates that digital infrastructure produces dual returns: it stabilises tourism activity during disruptions and supports broader economic adjustment.

Third, the tourism–growth results indicate that policymakers should place greater emphasis on shock prevention and downside protection than on expansion alone. Since negative tourism shocks generate stronger macroeconomic effects than positive tourism shocks generate gains, stabilisation policies should include targeted support for hospitality firms, emergency credit windows for tourism-dependent businesses, employment protection measures, and adaptive destination diversification strategies. Building buffers against downturns may yield larger welfare benefits than a narrow focus on maximising tourism volumes during normal periods.

Fourth, the exchange rate result suggests that macroeconomic stability remains critical for tourism resilience. Tourism policy cannot be designed in isolation from broader monetary, fiscal, and exchange rate management. In crisis conditions, exchange rate depreciation may amplify uncertainty rather than attract demand, implying that stable macroeconomic fundamentals are necessary to preserve destination credibility.

From this study, it is clear that resilient tourism recovery requires an integrated framework combining public health preparedness, digital transformation, macroeconomic stability, and targeted sectoral support. Tourism policy should therefore move beyond promotion-oriented strategies toward a resilience-oriented development model capable of managing future uncertainty shocks.

7. Future Research Directions

Several avenues for future research emerge from the findings of this study. First, extending the sample beyond December 2023 would allow researchers to assess whether

the adverse effects of COVID-19-induced fear dissipated fully during the recovery phase or whether longer-lasting scarring effects remained embedded in tourism demand and macroeconomic performance. A longer time horizon would also permit the analysis of post-pandemic normalisation and structural change in tourism behaviour.

Second, future studies could incorporate additional explanatory variables that capture the institutional, policy, environmental, and infrastructure dimensions of crisis response more directly. Variables such as vaccination rates, mobility restrictions, fiscal support measures, airline connectivity, tourism-specific stimulus programs, and environmental sustainability indicators may provide a more comprehensive explanation of recovery dynamics. Such extensions would also help disentangle whether tourism recovery was driven mainly by epidemiological improvement, policy intervention, digital adaptation, or broader macroeconomic normalisation.

Third, comparative cross-country research would be particularly valuable. Since the transmission of tourism shocks depends on economic structure, institutional quality, and the degree of tourism dependence, panel or multi-country nonlinear studies could identify why some economies absorb uncertainty shocks more successfully than others. This would enhance the external validity of the present findings and support broader theory building in the tourism–growth literature.

Fourth, future research may benefit from employing alternative nonlinear frameworks, including threshold models, regime-switching models, quantile ARDL approaches, or panel NARDL specifications. These techniques could provide richer evidence on whether the impact of tourism shocks differs across crisis intensity, development level, or stages of the business cycle.

Finally, future work should further investigate the channels through which tourism shocks affect economic growth. Disaggregated sectoral data on employment, transport, hospitality, digital services, and foreign exchange earnings could reveal the mechanisms that explain why negative tourism shocks are more macroeconomically damaging than positive tourism shocks are beneficial. Such evidence would significantly deepen both the empirical and policy relevance of the tourism resilience literature.

8. Conclusions

This study examined the impact of the COVID-19 Fear Index on tourism activity in India and further investigated the nonlinear relationship between tourism and economic growth while controlling for pandemic-related uncertainty using ARDL and NARDL models.

The results confirm a stable long-run relationship among tourism demand, pandemic-related fear, exchange rate, and ICT development. Empirical findings show that pandemic fear significantly reduces tourism demand, both in the long run and in the short run, highlighting the strong sensitivity of tourism to uncertainty shocks.

Exchange rate depreciation also negatively affects tourism demand, while ICT development contributes positively to tourism resilience and recovery.

The nonlinear growth analysis reveals a clear asymmetric tourism–growth relationship: positive tourism shocks increase economic growth, whereas negative shocks exert a stronger contractionary impact.

These findings underscore the vulnerability of tourism-dependent economies to crisis-driven uncertainty and highlight the importance of digital infrastructure, diversified tourism markets, and proactive crisis management policies to enhance sectoral resilience and macroeconomic stability.

The findings provide important evidence regarding the vulnerability of the tourism sector to fear-induced shocks and the asymmetric role of tourism in promoting economic

growth during periods of uncertainty. The study contributes to the literature in several ways. First, it incorporates the COVID-19 Fear Index into the tourism–growth framework for India, thereby capturing the psychological and uncertainty dimensions associated with the pandemic. Second, by employing a nonlinear approach, the study provides evidence that the relationship between tourism and economic growth cannot be adequately explained using conventional linear models. Third, the study offers new evidence from the Indian context, where tourism plays a significant role in employment generation, foreign exchange earnings, and economic development.

Despite these contributions, the study has several limitations. The analysis is limited to India and may not fully capture cross-country differences in tourism behaviour and pandemic responses. In addition, the COVID-19 Fear Index may not completely reflect all dimensions of uncertainty affecting tourism demand. Furthermore, the monthly GDP series was generated from annual data using cubic interpolation and should therefore be interpreted with caution. Future research may extend the analysis by incorporating additional uncertainty indicators and controls, conducting cross-country comparisons, or applying alternative nonlinear econometric techniques to further explore the tourism–growth nexus under crisis conditions.

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Abbreviations

Abbreviation	Definition
ARDL	Autoregressive Distributed Lag
COVID-19	Coronavirus Disease 2019
DW	Durbin–Watson Statistic
ECM	Error Correction Model
ECDC	European Centre for Disease Prevention and Control
FDI	Foreign Direct Investment
GDP	Gross Domestic Product
GFI	Global Fear Index
ICT	Information and Communication Technology
NARDL	Nonlinear Autoregressive Distributed Lag
PP	Phillips–Perron

VAR	Vector Autoregression
VECM	Vector Error Correction Model
WDI	World Development Indicator
Symbol	Definition
y_t	Real GDP per capita at time t
Tur_t	Tourist arrivals at time t
$COV19_t$	COVID-19 Global Fear Index at time t
ICT_t	Information and Communication Technology index
EXR_t	Nominal exchange rate
K_t	Capital stock
Tur_t^+	Positive tourism shocks
Tur_t^-	Negative tourism shocks
Δ	First difference operator
ECM_{t-1}	Error correction term
α	Long-run coefficient
β	Short-run coefficient
γ	Explanatory variable coefficient
ε_t	Error term
t	Time period
$\ln$	Natural logarithm

Appendix A. Derivation of the GFI for COVID-19

This appendix outlines the construction of the GFI, which serves as a proxy for pandemic-related uncertainty and public fear associated with COVID-19. The index combines information on global reported cases and deaths, capturing both the spread and severity of the pandemic (Makun, 2021). The construction of the GFI follows a three-step procedure.

- Step 1: RCI

The RCI measures the relative change in confirmed COVID-19 cases compared to the level observed fourteen days earlier. The 14-day lag reflects the widely recognised incubation period of the virus, defined as the time between exposure and symptom onset (WHO, 2020). This index captures the acceleration of infection dynamics and serves as an indicator of perceived pandemic risk.

The RCI is defined as:

$$RCI_t = \left[\frac{\sum_{i=1}^n c_{i,t}}{\sum_{i=1}^n (c_{i,t} + c_{i,t-14})} \right] \times 100 \quad (A1)$$

where RCI_t denotes the reported case index (RCI) at time t , $\sum_{i=1}^n c_{i,t}$ represents total COVID-19 cases across all regions at time t , and $\sum_{i=1}^n c_{i,t-14}$ denotes total cases recorded fourteen days earlier. The multiplication by 100 scales the index. Values approaching 100 indicate a rapid increase in infections and heightened pandemic risk, whereas values closer to zero indicate lower risk.

- Step 2: RDI

The RDI is constructed analogously to the RCI but focuses on mortality dynamics. It measures the change in reported COVID-19 deaths relative to the level observed fourteen days earlier, thereby reflecting the severity of the pandemic.

The RDI is given by:

$$RDI_t = \left[\frac{\sum_{i=1}^n d_{i,t}}{\sum_{i=1}^n (d_{i,t} + d_{i,t-14})} \right] \times 100 \quad (A2)$$

where RDI_t denotes the reported death index at time t , $\sum_{i=1}^n d_{i,t}$ represents total COVID-19 deaths across all regions at time t , and $\sum_{i=1}^n d_{i,t-14}$ denotes deaths recorded at the beginning of the incubation period. Similar to the RCI, higher values of the RDI indicate greater pandemic severity and heightened public concern.

- Step 3: GFI

The GFI aggregates the information contained in both the reported case and death indices to provide a comprehensive measure of pandemic-related uncertainty. Equal weights are assigned to both components, reflecting the joint importance of infection spread and mortality risk.

The GFI is defined as:

$$GFI_t = \frac{RCI_t + RDI_t}{2} \quad (A3)$$

where GFI_t represents the GFI at time t . By integrating information from both reported cases and deaths, the GFI provides a composite indicator of pandemic intensity and perceived risk. The index ranges from 0 to 100, where higher values indicate elevated levels of uncertainty and fear, while values closer to zero reflect relatively lower levels of concern.

In the context of this study, the GFI serves as a key explanatory variable capturing pandemic-induced uncertainty that influences tourism demand and economic activity. Higher levels of the index are expected to discourage travel behaviour and reduce tourism flows, thereby affecting broader macroeconomic performance.

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