

State Intervention and Spatial Inequality: Evaluating the Governance Effectiveness of Tourism Policy in Uttar Pradesh, India

Gaurav Agarwal^{*1}, Dr. Bhanu Pratap Pandey²

¹Research Scholar, Sharda School of Business Studies, Sharda University, Greater Noida, Uttar Pradesh, India,

Email ID: gaurav7777agarwal@gmail.com

²Assistant Professor, Sharda School of Business Studies, Sharda University, Greater Noida, Uttar Pradesh, India,

Email ID: bhanu.pandey@sharda.ac.in

***Corresponding Author**

Gaurav Agarwal

Research Scholar, Sharda School of Business Studies, Sharda University, Greater Noida, Uttar Pradesh, India,

Email ID: gaurav7777agarwal@gmail.com

ABSTRACT

How effectively do state governments translate spatial development objectives into policy outcomes, and under what institutional conditions does policy intervention succeed in correcting — rather than reinforcing — existing spatial inequalities? This study addresses these governance questions through a causal evaluation of Uttar Pradesh's 2018 and 2022 state-level development policies, using subnational visitor flows as a measurable outcome of spatial redistribution. Applying a continuous-treatment difference-in-differences framework — the first to use policy-document-derived treatment intensity — across all 75 districts over 2017–2022, we show that policy attention (measured as district mention frequency in official policy documents) generated no statistically significant average effect on domestic or foreign visitor arrivals. Heterogeneity analysis reveals a significant positive effect on foreign arrivals in medium-growth heritage districts under the 2022 policy, but high-growth religious destinations remain unresponsive, driven by place-specific pull factors that operate beyond the reach of state intervention. These findings support a structural policy reinforcement model: state development policies in spatially heterogeneous developing economies tend to amplify pre-existing destination hierarchies rather than correct them, reflecting a fundamental absorptive capacity constraint on governance effectiveness. The study contributes to public policy implementation theory, spatially differentiated governance, and the comparative political economy of subnational development in Asia.

KEYWORDS: Public policy implementation; spatial governance; subnational development policy; policy reinforcement; difference-in-differences; India; Uttar Pradesh; absorptive capacity

INTRODUCTION

A central challenge of spatial governance in developing economies is ensuring that state policy interventions correct, rather than entrench, existing inequalities in regional development. Subnational governments across Asia increasingly rely on sector-specific policy instruments — targeting infrastructure, investment, and promotion — to redirect economic activity toward lagging regions. Evaluating whether such instruments achieve their redistributive objectives is a fundamental question of governance effectiveness. Visitor-economy development has emerged as one such instrument, offering governments a policy lever for employment generation, infrastructure investment, and spatial redistribution of income (Joshi et al., 2016; Li et al., 2018). Yet the relationship between tourism policy and spatial development trajectories remains theoretically contested. Two competing models exist in the spatial policy literature. The **corrective model** holds that policy intervention redirects resources toward underperforming destinations, reducing spatial inequality over time (Uitermark et al., 2023). The reinforcement model holds that policy amplifies existing hierarchies, because

established destinations possess greater absorptive capacity, institutional ecosystems, and political visibility to translate policy signals into outcomes (Amore and Hall, 2024; Najam, 1995). Distinguishing between these models empirically requires causal identification — yet tourism policy evaluation in developing countries remains largely descriptive, relying on aggregate trends or qualitative assessments rather than quasi-experimental methods (Bhadeshiya and Prajapati, 2024; Thao, 2025). Uttar Pradesh (UP) provides a compelling setting to test these competing models. As India's most populous state, UP hosts an exceptionally diverse range of destinations from major religious centres such as Varanasi, Ayodhya, and Prayagraj to heritage sites, Buddhist circuits, and administrative hubs — generating substantial spatial variation in tourism demand and policy targeting (Das and Sharma, 2009; Shinde and Singh, 2023). Tourism activity is highly concentrated in a small number of districts, while many others experience limited visitor inflows (Awasthi and Nain, 2022). In response, the Government of Uttar Pradesh introduced successive tourism policies in 2018 and 2022, explicitly targeting spatial diversification and circuit development. Whether these interventions

corrected or reinforced existing spatial hierarchies is an open empirical question with direct implications for tourism governance across India and the broader developing world (Government of Uttar Pradesh, 2018, 2022).

This study addresses this question by evaluating the causal impact of UP's 2018 and 2022 tourism policies on district-level tourist arrivals using a continuous-treatment difference-in-differences (DiD) framework. A central methodological contribution is the construction of a **policy-document-derived continuous treatment variable** — the frequency with which each district is mentioned in official policy documents — which directly operationalises the spatial targeting logic embedded in policy design. This approach differs fundamentally from prior continuous-treatment applications in tourism (Milone et al., 2023), which use externally imposed aggregate proxies (COVID stringency indices) that vary over time but not by policy design intent. By measuring treatment as a district-varying, policy-derived intensity score, this study captures heterogeneity in policy attention that binary DiD specifications cannot detect, and provides a more direct test of whether policy targeting translates into tourism outcomes.

The empirical analysis yields three main findings. First, baseline DiD estimates show no statistically significant average effect of either the 2018 or 2022 policies on domestic or foreign tourist arrivals. Second, heterogeneity analysis reveals a positive and significant effect of the 2022 policy on foreign visits in medium-growth heritage destinations. Third, tourism growth in high-growth religious hubs is driven primarily by place-specific factors rather than policy intensity. Together, these findings support the structural reinforcement model over the corrective model.

These findings suggest that tourism policies in Uttar Pradesh have primarily reinforced existing spatial patterns of tourism development rather than altering them. The study makes three contributions. Empirically, it provides one of the first district-level causal evaluations of tourism policy in India using a DiD framework, extending prior applications in tourism policy contexts (Chi et al., 2018; Thao, 2025). Methodologically, it extends continuous-treatment DiD approaches to tourism research, capturing the full distribution of policy attention intensity rather than imposing a binary treated/untreated classification, and explicitly controls for episodic mega-events to isolate policy effects from event-driven demand shocks (Callaway et al., 2024; Milone et al., 2023). Theoretically, the findings contribute to spatial policy theory by demonstrating that state tourism interventions in UP have largely reinforced existing destination hierarchies — a pattern consistent with structural implementation gaps identified in tourism governance literature (Amore and Hall, 2024; Uitermark et al., 2023) — rather than generating balanced regional development.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature and outlines the policy context. Section 3 describes the Materials and Methods. Section 4 presents the empirical results. Section 5 discusses the findings, draws policy implications, and presents the conclusion.

SECTION 2: Literature Review and Policy Context

2.1 Policy Implementation and Tourism Policy Effectiveness

This study is grounded in policy implementation theory, which examines how policy intentions are translated into observable outcomes (Kirk et al., 2020; Nilsen, 2015). This perspective is particularly relevant in tourism, where policy outcomes depend on coordination across multiple levels of government and diverse private actors, often leading to gaps between stated objectives and realized impacts (Amore and Hall, 2024; Howlett, 2018).

Classical top-down models emphasise that effectiveness depends on clear objectives and effective administrative transmission (Montjoy and O'Toole, 1979), but Najam's (1995) framework extends this by highlighting that outcomes depend equally on context, institutional capacity, and stakeholder engagement. In tourism, these factors are particularly salient, as local administrative capacity, private sector participation, and access to infrastructure vary significantly across regions. Recent work in tourism governance further argues that implementation gaps are structural rather than exceptional, reflecting the mismatch between territorially uniform policies and spatially concentrated tourism demand (Amore and Hall, 2024).

In the context of Uttar Pradesh, where tourism development is unevenly distributed across districts, these theoretical insights suggest that policy effects may be limited or uneven. Accordingly, the first hypothesis is:

H1: Tourism policies (2018 and 2022) have a positive effect on district-level tourist arrivals.

2.2 Spatial Inequality and the Limits of Tourism Policy

Tourism development is inherently spatially uneven, tending to cluster in destinations with strong cultural, natural, or religious appeal (Shinde, 2022; Uitermark et al., 2023). Such spatial concentration is reinforced by infrastructure investment and promotion strategies that often favor already established destinations (Joshi et al., 2016; Uitermark et al., 2023).

In India, religious tourism plays a central role in shaping these patterns. Major destinations such as Varanasi, Ayodhya, and Prayagraj attract visitors primarily due to their religious significance, which operates independently of formal tourism policy (Bhadeshiya and Prajapati, 2024; Das and Sharma, 2009; Shinde, 2022). As a result, tourism growth in such locations may occur regardless of policy intervention, complicating the identification of policy effects.

These dynamics suggest a structural reinforcement mechanism: state tourism policies may systematically favour destinations that already possess the institutional capacity, infrastructure, and political visibility to absorb and respond to policy signals. This is consistent with Amore & Hall's (2024) concept of structural implementation gaps, whereby the mismatch between territorially uniform policy design and spatially concentrated tourism demand produces outcomes that mirror rather than alter existing hierarchies. Critically, this reinforcement mechanism has not been tested causally in the tourism literature. Existing studies document spatial concentration descriptively (Awasthi and Nain, 2022; Malhotra, 2024) but cannot distinguish whether

concentration reflects policy failure or the operation of structural reinforcement. A causal framework with district-level variation in policy exposure is required to adjudicate between the corrective and reinforcement models. This study provides that framework. Accordingly, the following hypotheses are proposed:

H2: The effect of tourism policy varies across districts, with medium-growth regions exhibiting greater responsiveness than high-growth or low-growth regions.

H3: Tourism growth in high-growth religious destinations is driven primarily by place-specific factors rather than policy intervention.

2.3 Difference-in-Differences in Tourism Policy Evaluation

The difference-in-differences (DiD) method is widely used to estimate the causal effects of policy interventions by comparing changes in outcomes between treated and less-treated units over time (Bertrand et al., 2004; Fredriksson and Oliveira, 2019). Its validity depends on the assumption that, in the absence of treatment, units would have followed similar trends—an assumption typically assessed using pre-treatment trend analysis (Baker et al., 2025; Callaway et al., 2024). Within tourism research, DiD has emerged as the preferred quasi-experimental approach for policy evaluation precisely because it does not require randomised assignment, making it well-suited to contexts where policies are implemented administratively across subnational units.

Applications of DiD in tourism research remain limited but are increasing. Prior studies have evaluated tourism promotion policies (Chi et al., 2018), national tourism initiatives (Gu, 2023), and infrastructure interventions such as high-speed rail (Bo and Ningqiao, 2017; Ren et al., 2023), with mixed findings. Some studies report positive impacts, particularly in less-developed regions, while others find limited or no effects when structural conditions are unfavourable (Albalade et al., 2017; Milone et al., 2023). Importantly, these findings underscore that null results can be substantively meaningful in policy evaluation — a null result in a well-specified DiD framework does not indicate an absence of information but rather provides evidence that the policy instrument failed to shift trajectories that were otherwise structurally determined.

Most existing DiD applications in tourism employ binary treatment specifications that obscure meaningful variation in policy exposure intensity across units. The methodologically proximate exception is Milone et al. (2023), which applies a continuous-treatment DiD framework to European Airbnb pricing during the COVID-19 pandemic, using national stringency indices as the continuous treatment variable. While this study demonstrates the applicability of continuous-treatment DiD in tourism contexts, its treatment variable is an externally imposed, time-varying aggregate measure that does not reflect deliberate spatial policy targeting by design. Stringency indices capture government responses to an exogenous health shock uniformly across subnational units; they do not vary by policy intent toward specific destinations or regions. As a result, the continuous variation in that setting is incidental to policy design rather than intrinsic to it.

The present study departs from this approach in a theoretically important way. Rather than using an external aggregate proxy, it constructs a **policy-document-derived, district-varying continuous treatment variable** based on the frequency with which each district is explicitly mentioned in official UP tourism policy documents. This operationalisation directly captures the spatial targeting logic embedded in policy design: districts mentioned more frequently are assumed to receive greater administrative focus, infrastructure prioritisation, and promotional support, reflecting the deliberate allocation of policy attention across the state's 75 districts. The continuous treatment variable therefore measures not merely exposure to a policy regime, but the intensity of intended policy engagement with each spatial unit — a conceptually distinct and more direct operationalisation of policy targeting than prior applications have employed. This approach is consistent with recent methodological guidance emphasising that policy measurement should reflect the mechanisms through which policy operates (Callaway et al., 2024; Schnake-Mahl et al., 2025).

The study most closely related to this research in substantive terms is Thao (2025), which applies a binary DiD framework to evaluate provincial-level tourism policy in Vietnam and finds no significant average policy effect. The present study builds on and extends this contribution in three specific ways. First, it operates at district level across 75 units, providing substantially finer spatial resolution and greater statistical power to detect heterogeneous effects. Second, and most critically, it replaces binary treatment classification with a continuous policy-intensity measure, enabling a more demanding test: rather than estimating whether being treated matters on average, it estimates whether the degree of policy attention matters across the full distribution of targeting intensity. A null result in this framework is therefore stronger and more informative than a binary DiD null — it indicates that no point in the distribution of policy attention, from minimally to heavily targeted districts, generated differential tourism growth. Third, it incorporates an explicit control for a major episodic mega-event — the 2019 Kumbh Mela — which prior DiD studies in tourism have not addressed, and which would otherwise confound policy estimates in religiously significant destinations (Chi et al., 2018; Thao, 2025).

The continuous treatment approach also provides the appropriate empirical framework for testing the structural reinforcement model introduced in Section 2.2. If the corrective model holds, the effect of policy attention intensity should be strongest in lower-baseline districts where unrealised growth potential exists. If the reinforcement model holds, the effect should be strongest in higher-baseline districts with greater absorptive capacity to respond to policy signals. Heterogeneity analysis across destination tiers — conducted in Section 4.3 — provides direct evidence on which model better characterises the relationship between policy targeting and tourism outcomes in Uttar Pradesh. Under this framework, the following hypotheses are tested:

H4: Districts receiving higher policy attention intensity experience greater growth in tourist arrivals relative to those receiving lower policy attention.

H5: The marginal effect of policy attention intensity on

tourist arrivals is positively associated with a district's baseline tourism volume, consistent with the structural reinforcement model rather than the corrective model.

2.4 Tourism Policy Evolution: 2018, and 2022

Uttar Pradesh's concentration of major religious, heritage, and cultural destinations — alongside deep spatial inequality in tourist flows — provides the context for successive state tourism policies since 2016 (Awasthi and Nain, 2022; Das and Sharma, 2009). Building on the foundational framework established by the 2016 Tourism Policy, the **Tourism Policy 2018** introduced a more explicit spatial strategy based on tourism circuits (Government of Uttar Pradesh, 2018). By linking destinations into thematic circuits—such as religious, heritage, and Buddhist circuits—the policy aimed to promote integrated regional development. It also expanded investment incentives and emphasized public-private partnerships. Importantly, the policy explicitly identified priority districts within these circuits, creating variation in policy attention across locations.

The **Tourism Policy 2022**, formulated in the post-COVID context, reflects both recovery priorities and evolving tourism dynamics (Government of Uttar Pradesh, 2022). It places greater emphasis on consolidating growth in major religious hubs while continuing efforts to expand tourism in less-developed regions. Key developments shaping this policy include the rising prominence of Ayodhya as a religious destination, improved international connectivity to the Buddhist circuit through Kushinagar, and the demonstrated impact of large-scale events such as the Kumbh Mela (Purswani and Bali, 2023; Sharma, 2026; Yadav et al., 2024). While the policy reiterates goals of spatial diversification, its emphasis on established destinations suggests a continued concentration of policy attention.

SECTION 3: MATERIALS AND METHODS

3.1 Data Sources and Panel Construction

This study combines three data sources. The primary dataset consists of district-level tourist arrivals obtained from the Uttar Pradesh Tourism Department, covering all 75 districts for the years 2017, 2018, 2019, 2020, and 2022 (Uttar Pradesh Tourism Department, n.d.). After merging with policy data, the final panel includes 375 observations.

District-level data for 2016, 2021, and 2023 are unavailable. As a result, 2017 serves as the baseline year, while 2021 is excluded due to the severe disruption caused by COVID-19. (District names used in this study follow the spellings appearing in the official Uttar Pradesh Tourism Department data and Government of UP policy documents. Where inconsistencies existed across official sources — a common feature of Indian administrative datasets, where district names are transliterated from Hindi and may vary across documents — the most frequently occurring or officially recognised spelling was adopted. Minor inconsistencies in district naming across datasets were corrected prior to merging.)

The second data source comprises the official tourism policy documents for 2016, 2018, and 2022 (Government of Uttar Pradesh, 2016, 2018, 2022). These documents are used to construct the treatment variables based on district

mention frequency.

The third dataset consists of regional hub-level tourism statistics for selected years (2016, 2021, 2023), used for descriptive analysis and to classify districts into growth tiers. While not used in the causal estimation, these data provide important context for interpreting spatial patterns in tourism growth.

3.2 Variables

Dependent variables. Two outcome variables are used: the natural logarithm of domestic tourist visits ($\ln DTV$) and foreign tourist visits ($\ln FTV$), both defined as $\log(\text{visits} + 1)$ to account for zero values. As a robustness check, the inverse hyperbolic sine transformation is also applied, yielding comparable results (Callaway et al., 2024; Chi et al., 2018).

Treatment variables. Policy exposure is measured using a continuous treatment approach based on district mention frequency. For each policy:

$$\text{treat2018}_{it} = \text{post2018}_t \times \text{mentions2018}_i$$

$$\text{treat2022}_{it} = \text{post2022}_t \times \text{mentions2022}_i$$

where post indicators capture the post-policy periods and mention counts reflect district-level policy attention. This specification allows estimation of the marginal effect of an additional policy mention on tourism outcomes.

Control variables. All models include district fixed effects and year fixed effects to control for time-invariant heterogeneity and common shocks. In addition, a dummy variable is included for the 2019 Kumbh Mela in Prayagraj to isolate the impact of this large-scale event (Mohanty et al., 2022; Yadav et al., 2024).

Heterogeneity classification. Districts are grouped into three categories based on regional hub growth patterns: high-growth (religious hubs), medium-growth (heritage and circuit-based destinations), and low-growth regions. Dummy variables for high- and medium-growth categories are interacted with treatment variables in the heterogeneity analysis.

3.3 Empirical Strategy

3.3.1 Baseline Model

The baseline specification follows a two-way fixed effects difference-in-differences model:

$$\ln(\text{Tourism}_{it}) = \alpha + \beta_1 \text{Treat2018}_{it} + \beta_2 \text{Treat2022}_{it} + \beta_3 \text{Kumbh}_{it} + \delta_i + \gamma_t + \epsilon_{it}$$

where Tourism_{it} denotes domestic or foreign tourist visits in district i and year t . District and year fixed effects are denoted by δ_i and γ_t , respectively. Standard errors are clustered at the district level (Bertrand et al., 2004).

The coefficients of interest, β_1 and β_2 , capture the average effect of policy exposure on tourism outcomes. A notable design feature of this specification is the explicit modelling of the 2019 Kumbh Mela as a separate event control. Prior DiD studies in tourism contexts have not accounted for episodic mega-events, which can generate large but temporary demand shocks that are unrelated to policy intervention (Chi et al., 2018; Thao, 2025). Failing to isolate such shocks risks confounding policy estimates, particularly in religiously significant destinations where periodic mass gatherings concentrate visitor flows. By explicitly separating event-driven demand from policy-

driven demand, this specification provides a cleaner identification of policy effects than would otherwise be possible.

3.3.2 Heterogeneity Analysis

To examine differential effects across regions, interaction terms are introduced:

$$\begin{aligned} \ln(\text{Tourism}_{it}) = & \alpha + \beta_1 \text{Treat2018}_{it} + \beta_2 \text{Treat2022}_{it} \\ & + \beta_3 (\text{Treat2018}_{it} \times \text{TierHigh}_i) \\ & + \beta_4 (\text{Treat2018}_{it} \times \text{TierMedium}_i) \\ & + \beta_5 (\text{Treat2022}_{it} \times \text{TierHigh}_i) \\ & + \beta_6 (\text{Treat2022}_{it} \times \text{TierMedium}_i) \\ & + \beta_7 \text{Kumbh}_{it} + \delta_i + \gamma_t + \epsilon_{it} \end{aligned}$$

3.3.3 Event Study

An event study specification is used to examine the dynamic effects of the 2018 policy:

$$\begin{aligned} \ln(\text{DTV}_{it}) = & \alpha + \sum_{t \neq 2017} \theta_t (\text{Year}_t \times \text{Mentions2018}_i) \\ & + \beta \text{Kumbh}_{it} + \delta_i + \gamma_t + \epsilon_{it} \end{aligned}$$

3.3.4 Robustness Checks

Three robustness checks are conducted. First, alternative outcome transformations using the inverse hyperbolic sine are applied. Second, the foreign tourism model is re-estimated using a restricted sample excluding districts with zero foreign tourist visits. Third, heterogeneity models are tested separately to confirm the stability of key results.

3.4 Data Limitations

Three limitations should be noted. First, the absence of pre-2017 district-level data limits the ability to establish a true pre-treatment baseline for the 2018 policy. Second, the exclusion of 2021 data, while methodologically justified due to COVID-19 disruptions, reduces temporal continuity. Third, the treatment variable—policy mention frequency—captures policy attention rather than actual resource allocation, and may not fully reflect on-the-ground investment patterns.

SECTION 4: RESULTS

4.1 Descriptive Patterns

The data reveal substantial spatial inequality in tourism growth between 2016 and 2023. Growth is heavily concentrated in a small number of religious hubs, particularly Varanasi and Ayodhya, while several regions exhibit limited or stagnant performance.

High-growth hubs are driven primarily by domestic religious tourism, with declining shares of foreign visitors. In contrast, some medium-growth regions, such as those associated with heritage and Buddhist circuits, show modest improvements in foreign tourist share. Low-growth regions remain largely disconnected from both domestic and international tourism circuits.

Overall, the descriptive evidence indicates that tourism growth in Uttar Pradesh has been uneven and largely shaped by destination-specific factors rather than broad-based spatial diversification.

4.2 Baseline DiD Results

Across all specifications, the policy variables for both 2018 and 2022 are statistically insignificant for domestic and foreign tourist visits. This indicates that, on average, districts receiving greater policy attention did not experience higher growth in tourist arrivals relative to less-targeted districts. Thus, **Hypothesis H1 is not supported**.

The control variables behave as expected. Year fixed effects capture the sharp decline in tourism during 2020 and the partial recovery by 2022, particularly for domestic tourism. Foreign tourism remains significantly below pre-pandemic levels. The Kumbh Mela variable is large and highly significant, confirming the importance of controlling for event-driven shocks.

Overall, the baseline results suggest that tourism policies did not have a measurable average impact on district-level tourism outcomes.

4.3 Heterogeneity Analysis

For **domestic tourism**, no statistically significant policy effects are observed across any category of districts. The null result is therefore consistent across high-, medium-, and low-growth regions.

For **foreign tourism**, the results differ. While the average effect remains insignificant, a positive and statistically significant effect emerges for medium-growth regions under the 2022 policy. This suggests that districts associated with heritage and circuit-based tourism experienced modest gains in foreign tourist visits in response to policy attention.

In contrast, high-growth religious hubs do not exhibit significant policy effects, consistent with the argument that tourism growth in these regions is driven primarily by place-specific factors. Low-growth regions show no positive response.

These findings provide **partial support for H2** and are consistent with **H3**, indicating that policy responsiveness varies across destination types and is limited in areas where tourism demand is driven by strong underlying pull factors. The baseline results also fail to support Hypothesis **H4**: districts receiving higher policy attention did not experience systematically greater growth in tourist arrivals relative to less-targeted districts, as evidenced by the statistically insignificant treatment coefficients across all specifications. The pattern of effects — significant only in medium-growth destinations, absent in high- and low-growth tiers — is inconsistent with the corrective model and provides directional support for **H5**, suggesting that policy responsiveness is positively associated with baseline destination capacity.

4.4 Event Study

The coefficients across all post-treatment years are statistically insignificant for both domestic and foreign tourism. There is no evidence of a delayed or dynamic policy effect over time. The flat post-treatment trajectory indicates that tourism growth paths were determined by underlying structural factors rather than altered by policy targeting intensity, consistent with the structural reinforcement model.

4.5 Robustness Checks

First, alternative transformations of the dependent variables yield consistent estimates. Second, restricting the foreign tourism sample to districts with positive tourist inflows does not alter the findings. Third, the heterogeneity results remain stable across alternative model specifications.

SECTION 5: DISCUSSION

5.1 Interpreting the Null Result: Policy Following Tourism Rather Than Leading It

The central finding of this study — that UP's tourism policies produced no statistically significant average effect on district-level tourist arrivals across either the 2018 or 2022 intervention periods — is theoretically interpretable rather than merely negative. Taken together with the heterogeneity results, it provides empirical support for the structural reinforcement model over the corrective model introduced in Section 2.2. Tourism growth in Uttar Pradesh during 2017–2022 was primarily driven by structural forces — religious pull factors, periodic mega-events, and infrastructure developments — that operate largely independently of policy targeting intensity. Districts with the greatest underlying demand potential grew regardless of policy attention; districts with the weakest structural foundations did not respond even when targeted. This pattern is precisely what the reinforcement model predicts: policy amplifies trajectories already in motion rather than generating new ones.

This finding advances a specific theoretical argument: in spatially heterogeneous developing economies where tourism demand is concentrated in destinations with deep cultural, religious, or heritage significance, state-level tourism policy faces a fundamental absorptive capacity constraint. Destinations with institutional ecosystems capable of translating policy signals into outcomes — accommodation capacity, transport connectivity, hospitality labour markets — are precisely those where tourism would grow regardless of policy. Destinations lacking these complements cannot respond to policy attention alone. The policy therefore follows tourism rather than leading it, not because of poor design, but because of a structural mismatch between policy instruments and destination readiness.

5.2 The Exception: Medium-Growth Hubs and Foreign Tourism

Against this broader null effect, the significant positive impact of the 2022 policy on foreign tourist visits in medium-growth hubs provides an important qualification. This result identifies the conditions under which policy attention can generate measurable outcomes.

Medium-growth hubs such as Agra and Gorakhpur occupy an intermediate position between high-demand religious centres and low-demand administrative districts. They possess internationally recognised assets—the Taj Mahal and Mughal heritage circuit in Agra, and the Buddhist circuit centred on Kushinagar in Gorakhpur—while also serving foreign tourist markets that are more responsive to policy interventions than domestic pilgrimage flows.

In Agra, policy emphasis on heritage conservation, international marketing, and visitor experience aligns with

destination needs during a period of post-pandemic recovery. In Gorakhpur, the interaction between policy attention and infrastructure expansion, particularly the Kushinagar International Airport, creates a complementary environment for foreign tourism growth. These findings support the argument that policy interventions are most effective in destinations with sufficient baseline capacity but not yet fully saturated (Albalade et al., 2017; Bo and Ningqiao, 2017; Ren et al., 2023).

The negative baseline coefficient for low-growth hubs in the foreign tourism model reflects compositional differences in visitor type — business travellers in districts such as Lucknow and Kanpur recovered more slowly than leisure tourists post-pandemic — rather than any policy-induced decline (Arshad et al., 2021).

5.3 The Kumbh Mela Effect: Event-Driven Versus Policy-Driven Growth

The magnitude of the Kumbh Mela effect also validates the methodological decision to model it explicitly as a separate control rather than allowing it to be absorbed into the error term or the year fixed effects, which would have produced biased estimates for the Prayagraj hub in particular. Estimated coefficients imply increases of approximately 440% in domestic and 494% in foreign tourist visits in Prayagraj during the 2019 Kumbh Mela, far exceeding any plausible policy effect.

This finding highlights two key points. First, it validates the need to model such events explicitly to avoid confounding policy estimates. Second, it reinforces the distinction between demand creation and demand facilitation. While policy can support large-scale events through infrastructure and management, it does not generate the underlying religious demand that drives participation (Mohanty et al., 2022; Yadav et al., 2024).

5.4 COVID-19, Recovery, and the Timing of Policy Evaluation

The evaluation of the 2022 policy is shaped by the broader context of COVID-19 disruption and uneven recovery. Tourism activity declined sharply in 2020, with domestic visits falling by approximately 66% and foreign visits by 77%. By 2022, domestic tourism had largely recovered, while foreign tourism remained significantly depressed.

This asymmetric recovery complicates causal interpretation. The 2022 policy is evaluated over a single post-treatment year, making it difficult to separate policy effects from recovery dynamics. As Howlett (2018) notes, policy impacts often emerge with temporal lags, particularly when implemented during periods of economic disruption.

Preliminary trends suggest recovery in medium-growth hubs, but the available data does not allow definitive attribution of these changes to policy rather than broader global recovery processes (Arshad et al., 2021; Gupta et al., 2021). Longer post-treatment time series are therefore essential for robust evaluation.

5.5 Implications for Policy Implementation Theory

From a policy implementation perspective, the null result reflects misalignment across key dimensions identified in Najam's (1995) framework. Policy content is conceptually sound but lacks operational specificity regarding resource

allocation and implementation mechanisms (Amore and Hall, 2024; Awasthi and Nain, 2022). Contextual factors — including the dominance of religious tourism and pandemic disruption — further concentrated outcomes toward already dominant destinations. Capacity limitations at the district level constrained effective execution, while less-developed districts lacked access to the institutional support needed to translate policy attention into visitor growth (Howlett, 2018; Kirk et al., 2020).

Collectively, these factors produce a system in which policy ambition is not matched by implementation capability. Comparative evidence from contexts where DiD has detected positive tourism policy effects — notably Japan (Chi et al., 2018) and China (Gu, 2023) — suggests that success is associated with clearly defined financial commitments and implementation mechanisms, conditions that UP's framework-oriented policies do not yet meet.

5.6 Contributions, Limitations, and Future Research

This study makes three contributions to public policy and governance scholarship. Theoretically, it provides the first causal empirical test of the corrective versus reinforcement models of subnational development policy in the Asian context, finding consistent support for the reinforcement model across two policy cycles and 75 administrative districts. This advances implementation theory by demonstrating that governance gaps are not random failures but structurally predictable outcomes of the mismatch between uniform policy instruments and heterogeneous local absorptive capacity — a finding with direct relevance to spatially differentiated governance debates across South and Southeast Asia. Methodologically, it introduces a policy-document-derived continuous treatment variable into quasi-experimental policy evaluation, providing a more direct operationalisation of government targeting intent than prior applications of difference-in-differences in this context. Empirically, it provides one of the first district-

level causal evaluations of a state-level development policy in India, generating evidence with clear implications for spatially differentiated governance strategies across the region.

These contributions carry specific governance implications. For event-dependent destinations such as Prayagraj, policy should prioritise increasing visitor spending and duration during peak gatherings rather than attempting to sustain event-level volumes across non-event years.

However, limitations remain. The absence of pre-2016 data constrains baseline estimation; the short post-2022 window limits inference; the treatment proxy may not fully capture actual resource allocation; and the focus on visitor numbers excludes economic impact measures. Addressing these limitations requires extended datasets, improved measurement, and broader outcome indicators. Overall, the findings highlight a central implication: effective tourism policy in spatially heterogeneous contexts requires alignment with structural demand conditions, differentiated targeting, and realistic expectations regarding policy influence. Advances in data availability and quasi-experimental methods create a strong foundation for more evidence-based tourism governance in India.

TABLE 1 Caption:

Table 1. Distribution of Policy Mention Scores by District and Regional Hub Tier, UP Tourism Policies 2018 and 2022.

Note: Mention scores represent the frequency with which each district name appears in the respective official policy document (Government of Uttar Pradesh, 2018, 2022). Hub tier classification is based on 2016–2023 regional hub growth rates derived from UP Tourism Department regional office data. High-growth hubs: Varanasi, Ayodhya, Prayagraj. Medium-growth hubs: Agra, Gorakhpur. Low-growth hubs: Lucknow, Meerut, Bareilly, Jhansi

District	Hub	Tier	Mentions 2018	Mentions 2022
Ayodhya (Faizabad)	Ayodhya	High	15	3
Balrampur	Ayodhya	High	5	2
Shravasti	Ayodhya	High	4	2
Amethi	Ayodhya	High	2	1
Barabanki	Ayodhya	High	2	1
Baharaich	Ayodhya	High	2	1
Gonda	Ayodhya	High	1	1
Ambedkarnagar	Ayodhya	High	0	1
Sultanpur	Ayodhya	High	0	1
Prayagraj (Allahabad)	Prayagraj	High	15	6
Kaushambi	Prayagraj	High	6	2
Fatehpur	Prayagraj	High	1	2
Pratapgarh	Prayagraj	High	1	1
Varanasi	Varanasi	High	13	7

District	Hub	Tier	Mentions 2018	Mentions 2022
Sonbhadra	Varanasi	High	7	2
Mirzapur	Varanasi	High	7	4
Chandauli	Varanasi	High	2	2
Sant Ravidas Nagar (Bhadohi)	Varanasi	High	1	1
Ghazipur	Varanasi	High	1	1
Jaunpur	Varanasi	High	0	2
Hub Subtotal — High			67	38
Hub Mean — High			4.25	2.15
Mathura	Agra	Medium	19	5
Agra	Agra	Medium	13	8
Aligarh	Agra	Medium	1	2
Firozabad	Agra	Medium	1	2
Etah	Agra	Medium	1	3
Mainpuri	Agra	Medium	0	2
Kasganj	Agra	Medium	0	1
Hathras	Agra	Medium	0	2
Gorakhpur	Gorakhpur	Medium	9	4
Siddharthnagar	Gorakhpur	Medium	5	3
Kushinagar (Padrauna)	Gorakhpur	Medium	4	2
Maharajganj (Sunoli)	Gorakhpur	Medium	3	1
Sant Kabirnagar	Gorakhpur	Medium	2	1
Baliya	Gorakhpur	Medium	1	2
Azamgarh	Gorakhpur	Medium	0	1
Basti	Gorakhpur	Medium	0	2
Devaria	Gorakhpur	Medium	0	1
Mau	Gorakhpur	Medium	0	1
Hub Subtotal — Medium			59	42
Hub Mean — Medium			3.28	2.33
Chitrakoot	Jhansi	Low	10	4
Lalitpur	Jhansi	Low	4	4
Banda	Jhansi	Low	4	3
Jhansi	Jhansi	Low	3	2
Mahoba	Jhansi	Low	2	2
Jalaun (Urai)	Jhansi	Low	0	4
Hamirpur	Jhansi	Low	0	4
Lucknow	Lucknow	Low	12	2
Sitapur	Lucknow	Low	8	2
Kanpur Nagar	Lucknow	Low	5	1
Farrukhabad	Lucknow	Low	4	1
Lakhimpur Khiri	Lucknow	Low	3	2
Rae-Bareilly	Lucknow	Low	2	1
Unnao	Lucknow	Low	2	2
Hardoi	Lucknow	Low	2	1
Etawah	Lucknow	Low	1	1
Auraiya	Lucknow	Low	1	1
Kannauj	Lucknow	Low	0	0

District	Hub	Tier	Mentions 2018	Mentions 2022
Kanpur Dehat	Lucknow	Low	0	1
Saharanpur	Meerut	Low	3	2
Bagpat	Meerut	Low	3	2
Hapur	Meerut	Low	3	2
Gautam Buddhnagar	Meerut	Low	3	0
Bulandshahar	Meerut	Low	2	1
Muzaffarnagar	Meerut	Low	2	1
Meerut	Meerut	Low	2	1
Ghaziabad	Meerut	Low	1	1
Shamli	Meerut	Low	0	1
Bareilly	Bareilly	Low	1	1
Budaun	Bareilly	Low	1	0
Bijnor	Bareilly	Low	1	2
Pilibhit	Bareilly	Low	1	1
Shahjahanpur	Bareilly	Low	0	2
Sambhal	Bareilly	Low	0	1
Moradabad	Bareilly	Low	0	1
Rampur	Bareilly	Low	0	1
Amroha (Jyotibaphule Nagar)	Bareilly	Low	0	1
Hub Subtotal — Low			86	58
Hub Mean — Low			2.32	1.57
All Districts Total			212	138
All Districts Mean			2.83	1.84

TABLE 2Caption:

Table 2. Regional Hub Tourism Performance, Uttar Pradesh, 2016–2023.

Note: Total arrivals data for 2016 and 2021 are sourced from UP Tourism Department regional office records. Total arrivals for 2023 are sourced from UP Tourism Department annual statistics (Uttar Pradesh Tourism

Department, n.d.). The Lucknow Region 2023 total is corrected to the sum of domestic and foreign components (23,901,179) due to a source-level discrepancy with the reported aggregate figure. Growth rate is calculated as percentage change in total arrivals between 2016 and 2023. Foreign share is calculated as foreign arrivals as a percentage of total arrivals in the respective year.

Hub	Growth Tier	Total Arrivals 2016	Total Arrivals 2021	Total Arrivals 2023	Growth 2016–2023 (%)	Foreign Share 2016 (%)	Foreign Share 2023 (%)
Varanasi	High	17,511,717	6,884,084	129,405,720	639.0	4.23	0.17
Bareilly	Low	11,627,701	717,181	37,030,764	218.5	0.04	0.04
Lucknow	Low	8,226,118	10,917,340	23,901,179	190.6	1.40	0.05
Ayodhya	High	21,804,393	19,497,216	63,010,176	189.0	0.66	0.01
Jhansi	Low	16,923,331	6,837,685	31,619,341	86.8	0.89	0.01
Agra	Medium	63,740,422	37,170,456	105,030,099	64.8	2.53	1.05
Prayagraj	High	42,806,944	14,492,831	53,935,319	26.0	0.31	0.01
Meerut	Low	22,331,685	11,357,038	24,534,984	9.9	0.25	0.03
Gorakhpur	Medium	11,728,705	1,879,341	11,659,609	−0.6	1.68	1.98
Total UP		216,701,016	109,753,172	480,127,191	121.6	1.46	0.33

TABLE 3 Caption:

Table 3. Baseline DiD Results: Effect of Tourism Policy Targeting Intensity on Tourist Visits, Uttar Pradesh

Districts, 2017–2022.

Note: Dependent variables are the natural logarithm of domestic tourist visits ($\ln_dtv$) and foreign tourist visits

(ln_ftv), constructed as $\log(\text{visits} + 1)$. All models include district and year fixed effects. Standard errors are clustered at the district level and reported in parentheses. $\text{treat2018} = \text{post2018} \times \text{mentions2018}$; $\text{treat2022} = \text{post2022} \times \text{mentions2022}$, where mentions represent the

count of district appearances in the respective policy document. kumbh_2019 is an indicator variable equal to 1 for Prayagraj district in 2019. Reference year: 2017. Reference district: Agra. N = 375 (75 districts $\times$ 5 years). *** p < 0.001, ** p < 0.01, * p < 0.05.

Variable	ln(DTV) Model 1	ln(FTV) Model 2
treat2018	0.027 (0.022)	0.005 (0.028)
treat2022	0.061 (0.115)	-0.262 (0.276)
kumbh_2019	1.684*** (0.174)	1.779*** (0.369)
Year FE: 2018	0.169* (0.072)	0.253 (0.160)
Year FE: 2019	0.270*** (0.072)	0.356* (0.174)
Year FE: 2020	-1.218*** (0.131)	-1.454*** (0.324)
Year FE: 2022	0.557 (0.297)	-2.359*** (0.656)
District FE	Yes	Yes
Observations	375	375
R-squared	0.869	0.853
Adj. R-squared	0.833	0.812

TABLE 4Caption:

Table 4. Heterogeneity DiD Results: Policy Effects by Regional Hub Growth Tier, Uttar Pradesh Districts, 2017–2022.

Note: Dependent variables are the natural logarithm of domestic tourist visits (ln_dtv) and foreign tourist visits (ln_ftv). All models include district and year fixed effects with standard errors clustered at district level in parentheses. Low-growth hubs (Lucknow, Meerut, Bareilly, Jhansi) serve as the reference tier category.

treat2018_high and treat2022_high are interactions of the respective treatment variable with an indicator for high-growth hub districts (Varanasi, Ayodhya, Prayagraj). treat2018_medium and treat2022_medium are interactions with an indicator for medium-growth hub districts (Agra, Gorakhpur). Total policy effect for medium-growth hubs after 2022 policy on FTV = $\text{treat2022} + \text{treat2022_medium} = -0.940 + 1.090 = +0.150$. N = 375. *** p < 0.001, ** p < 0.01, * p < 0.05

Variable	ln(DTV) Model 3	ln(FTV) Model 4
treat2018	0.106 (0.082)	0.032 (0.067)
treat2022	0.252 (0.197)	-0.940** (0.359)
treat2018_high	-0.084 (0.078)	-0.025 (0.060)
treat2018_medium	-0.104 (0.077)	-0.050 (0.063)
treat2022_high	-0.165 (0.230)	0.431 (0.423)
treat2022_medium	-0.254 (0.208)	1.090*** (0.314)
kumbh_2019	1.728*** (0.291)	1.511** (0.566)
Year FE: 2018	0.104 (0.091)	0.236 (0.170)
Year FE: 2019	0.205* (0.088)	0.343 (0.185)
Year FE: 2020	-1.283*** (0.141)	-1.470*** (0.337)
Year FE: 2022	0.362 (0.316)	-1.936** (0.714)
District FE	Yes	Yes
Observations	375	375
R-squared	0.874	0.864
Adj. R-squared	0.837	0.825

TABLE 5 Caption:

Table 5. Robustness Checks: Alternative Specifications for Baseline DiD Models.

Note: Model 5 uses inverse hyperbolic sine transformation IHS(DTV) as dependent variable. Model 6 uses IHS(FTV). Models 7 and 8 exclude all 41 districts

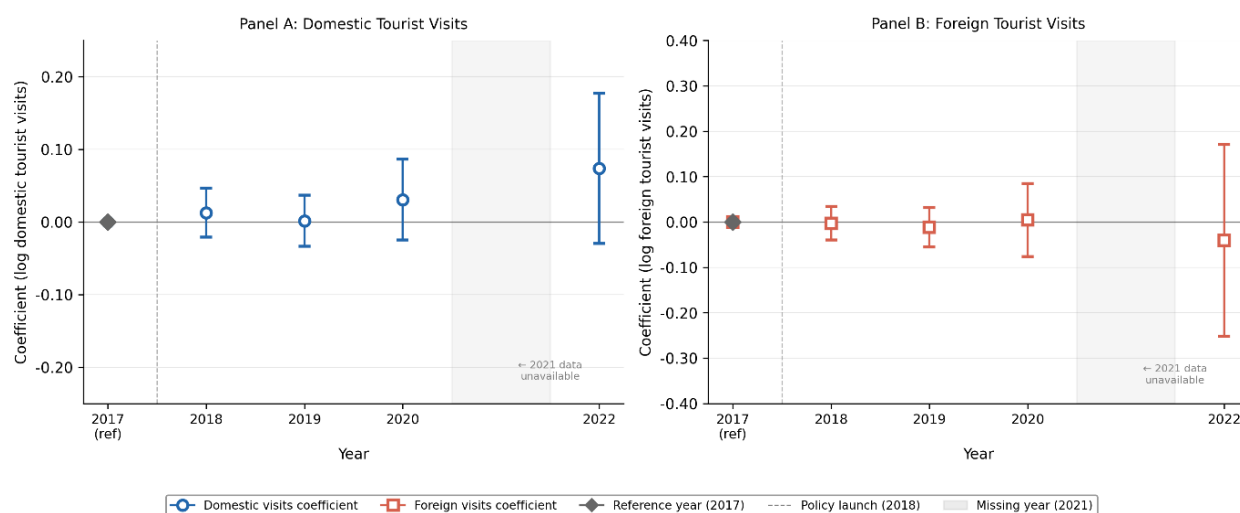
with zero foreign tourist visits in any year, retaining 170 observations across 34 districts. All models include district and year fixed effects with standard errors clustered at district level in parentheses. *** p < 0.001, ** p < 0.01, * p < 0.05.

Variable	IHS(DTV) Model 5	IHS(FTV) Model 6	ln(FTV) No-Zero Model 7
treat2018	0.027 (0.022)	0.005 (0.030)	0.017 (0.012)
treat2022	0.061 (0.115)	-0.277 (0.301)	0.072 (0.175)
kumbh_2019	1.684*** (0.174)	1.681*** (0.400)	2.399*** (0.220)
Year FE: 2018	0.169* (0.072)	0.269 (0.176)	0.032 (0.064)
Year FE: 2019	0.270*** (0.072)	0.383* (0.193)	0.080 (0.100)
Year FE: 2020	-1.218*** (0.131)	-1.493*** (0.350)	-1.615*** (0.193)
Year FE: 2022	0.557 (0.297)	-2.522*** (0.712)	-2.425*** (0.648)
District FE	Yes	Yes	Yes
Observations	375	375	170
R-squared	0.869	0.847	0.888
Adj. R-squared	0.833	0.805	0.853

Figure 1. Event study estimates of the dynamic effect of 2018 tourism policy mention intensity on district-level tourist visits, Uttar Pradesh, 2017–2022. Panel A presents coefficients for log domestic tourist visits; Panel B presents coefficients for log foreign tourist visits. Each coefficient represents the interaction between an indicator for the respective year and the district-level 2018 policy mention score, with 2017 as the reference year. All models include district and year fixed effects. Error bars represent 95% confidence intervals based on standard errors clustered at the district level. The reference year

coefficient is zero by construction. The gap between 2020 and 2022 reflects the unavailability of district-level data for 2021. The vertical dashed line marks the 2018 policy launch. The flat and statistically insignificant pattern of coefficients across all post-treatment years supports the null hypothesis of no systematic relationship between policy targeting intensity and tourist visit growth trajectories. N = 375 (75 districts × 5 years). Source: Authors' calculations based on UP Tourism Department data and Government of UP policy documents (2018; 2022).

Figure 1. Event Study: Dynamic Effects of 2018 Policy Mention Intensity on District-Level Tourist Visits, Uttar Pradesh (Reference Year: 2017)



REFERENCES:

1. Albalade D, Campos J and Jiménez JL (2017) Tourism and high speed rail in Spain: Does the AVE increase local visitors? *Annals of Tourism Research* 65: 71–82.
2. Amore A and Hall CM (2024) Policy Failures, Action and Implementation Gaps, and Non-Policy in Tourism. *Tourism Interventions*: 212–224.
3. Arshad MO, Khan S, Haleem A, et al. (2021)

- Understanding the impact of Covid-19 on Indian tourism sector through time series modelling. *Journal of Tourism Futures* 9(1): 101–115.
4. Awasthi A and Nain A (2022) Uttar Pradesh Tourism Policy 2018: How Effective and Efficient Can It Be? *Domestic Tourism and Hospitality Management*, 163–174. Available at: <https://doi.org/10.1201/9781003283331-11>.
5. Baker A, Callaway B, Cunningham S, et al. (2025) Difference-in-differences designs: A practitioner's

- guide. Available at: <https://arxiv.org/abs/2503.13323>.
6. Bertrand M, Duflo E and Mullainathan S (2004) How Much Should We Trust Differences-In-Differences Estimates? *The Quarterly Journal of Economics* 119(1): 249–275.
7. Bhadeshiya H and Prajapati U (2024) Religious Tourism: An Insight Into the Government's Efforts to Promote "Incredible India. *Tourism Planning and Destination Marketing* 2nd Edition: 237–258.
8. Bo Z and Ningqiao L (2017) The impact of high-speed trains on regional tourism economies. *Tourism Economics* 24(2): 187–203.
9. Callaway B, Goodman-Bacon A and Sant'Anna PH (2024) Difference-in-differences with a Continuous Treatment. w32117. Cambridge, MA: National Bureau of Economic Research. Available at: <http://www.nber.org/papers/w32117.pdf> (accessed 19 April 2026).
10. Chi P-Y, Chang T, Takahashi D, et al. (2018) Evaluation of the impact of the tourism nation promotion project on inbound tourists in Japan: a difference-in-differences approach. *Asia Pacific Journal of Tourism Research* 24(1): 31–55.
11. Das D and Sharma SK (2009) An assessment of the impact of tourism development at Varanasi: perspectives of local tourism businesses. *International Journal of Tourism Policy* 2(3): 167.
12. Fredriksson A and Oliveira GM de (2019) Impact evaluation using Difference-in-Differences. *RAUSP Management Journal* 54(4): 519–532.
13. Government of Uttar Pradesh (2016) Uttar Pradesh Tourism Policy 2016. Available at: <https://www.airda.org/assets/docs/up-tourism-policy-2016.pdf>.
14. Government of Uttar Pradesh (2018) Uttar Pradesh Tourism Policy 2018. Invest UP. Available at: <https://invest.up.gov.in/wp-content/themes/investup/pdf/U-P-Tourism-Policy-2018-compressed-min.pdf>.
15. Government of Uttar Pradesh (2022) Uttar Pradesh Tourism Policy 2022. Invest UP. Available at: https://invest.up.gov.in/wp-content/uploads/2023/02/Tourism_Policy_2022.pdf.
16. Gu J (2023) The impact of national tourism day festivals on inbound tourism: A spatial difference-in-differences approach. *Tourism Economics* 30(2): 417–441.
17. Gupta V, Cahyanto I, Sajnani M, et al. (2021) Changing dynamics and travel evading: a case of Indian tourists amidst the COVID 19 pandemic. *Journal of Tourism Futures* 9(1): 84–100.
18. Howlett M (2018) Moving policy implementation theory forward: A multiple streams/critical juncture approach. *Public Policy and Administration* 34(4): 405–430.
19. Joshi O, Poudyal NC and Larson LR (2016) The influence of sociopolitical, natural, and cultural factors on international tourism growth: a cross-country panel analysis. *Environment, Development and Sustainability* 19(3): 825–838.
20. Kirk N, Robson-Williams M, Fenemor A, et al. (2020) Exploring the barriers to freshwater policy implementation in New Zealand. *Australasian Journal of Water Resources* 24(2): 91–104.
21. Li KX, Jin M and Shi W (2018) Tourism as an important impetus to promoting economic growth: A critical review. *Tourism Management Perspectives* 26: 135–142.
22. Malhotra TJ (2024) Central Government Initiatives and Strategies in Temple Tourism in India: A Critical Analysis. In: *International Handbook of Skill, Education, Learning, and Research Development in Tourism and Hospitality*, pp. 1145–1159.
23. Milone FL, Gunter U and Zekan B (2023) The pricing of European Airbnb listings during the pandemic: A difference-in-differences approach employing COVID-19 response strategies as a continuous treatment. *Tourism Management* 97: 104738.
24. Mohanty P, Himanshi and Choudhury R (2022) Events Tourism in the Eye of the Covid-19 Storm: Impacts and Implications. In: *Event Tourism in Asian Countries*, pp. 97–114. Available at: <https://doi.org/10.1201/9781003161134-6>.
25. Montjoy RS and O'Toole LJ (1979) Toward a Theory of Policy Implementation: An Organizational Perspective. *Public Administration Review* 39(5): 465.
26. Najam A (1995) Learning from the literature on policy implementation: A synthesis perspective (IIASA Working Paper WP-95-061. International Institute for Applied Systems Analysis. Epub ahead of print 1995.
27. Nilsen P (2015) Making sense of implementation theories, models and frameworks. *Implementation Science* 10(1).
28. Purswani S and Bali B (2023) Mediating Cultural Heritage Revival Through Urban Transformation in Ayodhya City. Available at: <https://doi.org/10.4324/9781003342441-20>.
29. Ren X, Zeng G, Dong K, et al. (2023) How does high-speed rail affect tourism development? The case of the Sichuan-Chongqing Economic Circle. *Transportation Research Part A: Policy and Practice* 169: 103588.
30. Schnake-Mahl A, Diez Roux AV, Bilal U, et al. (2025) Rigorous policy measurement: causal inference challenges and opportunities. *American Journal of Epidemiology* 194(11): 3099–3105.
31. Sharma P (2026) Pilgrimage to prosperity: measuring the tourism-led economic transformation of Ayodhya following the construction of the Shri Ram Temple in India. Available at: <https://doi.org/10.1080/13683500.2026.2659797>.
32. Shinde K and Singh RPB (2023) Still on UNESCO's "Tentative List of World Heritage"? Heritage, Tourism, and Stunted Growth in Sarnath (Varanasi, India. *Heritage* 6(7): 5051–5065.
33. Shinde KA (2022) How Effective Is a Buddhist Pilgrimage Circuit as a Product and Strategy for Heritage Tourism in India? *Heritage* 5(4): 3846–3863.
34. Thao HTP (2025) Tourism policy in Vietnam: An evaluation using the difference-in-differences model. *Journal of Policy Research in Tourism, Leisure and Events* 17(3): 656–679.

35. Uitermark J, Hochstenbach C and Groot J (2023) Neoliberalization and urban redevelopment: the impact of public policy on multiple dimensions of spatial inequality. *Urban Geography* 45(4): 541–564.
36. Uttar Pradesh Tourism Department (n.d.) Year-wise tourist statistics — Uttar Pradesh. In: Government of Uttar Pradesh. Available at: <https://uptourism.gov.in/en/post/Year-wise-Tourist-Statistics>.
37. Yadav D, Mahato S, Choudhary A, et al. (2024) Cultural heritage and urban morphology: land use transformation in ‘Kumbh Mela’ of Prayagraj, India. *Frontiers of Urban and Rural Planning* 2(1).