

Research on the Influence Mechanism and Effects of Digital Economy on Carbon Emissions from Urban Tourism in China

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Abstract. Amid growing international efforts to address climate change and China's commitment to its carbon peak and carbon neutrality targets, transforming the tourism sector toward low-carbon practices is now critical to advancing sustainable and high-quality economic growth. As a new engine of structural transformation, the digital economy may help address the carbon-intensive growth of the tourism sector, yet its effects and underlying mechanisms remain unclear. This study examines the impact of China's digital economy on urban tourism carbon emissions using panel data from 282 prefecture-level cities from 2005 to 2023. Results show that the digital economy significantly reduces total tourism carbon emissions but initially increases carbon emission intensity. The relationship between the digital economy and tourism-related carbon emissions follows a nonlinear inverted U-curve pattern. Mechanism analysis reveals three pathways: (1) energy-efficiency improvement through technological innovation, (2) rebound effects driven by market expansion, and (3) structural upgrading through industrial integration. The overall effect therefore depends on the evolving balance between efficiency gains and scale expansion. Regional heterogeneity is also evident: the emission-reduction effect is strongest in eastern China, weaker in central China, and turns positive in western China in the short term. These findings provide empirical evidence for understanding the environmental consequences of digital transformation in tourism and offer policy implications for designing region-specific digital and low-carbon transition strategies.

Keywords: Digital Economy, Tourism Carbon Emissions, Emission Reduction Mechanisms, Nonlinear Effect, Regional Heterogeneity

1. Introduction

As global climate action intensifies and China advances its 2030 carbon peak and 2060 carbon neutrality goals, low-carbon tourism has become a key lever for sustainable and high-quality development. As a service industry, tourism has experienced extensive growth, with carbon emissions rising across its industry chain and showing signs of weak decoupling and carbon lock-in

[1]. Meanwhile, global initiatives such as the Glasgow Declaration and China's "dual-carbon" targets have accelerated the tourism industry's green transition [2]. Digital technologies—including big data and AI—are transforming tourism supply and demand, offering new avenues to cut carbon emissions from tourism. However, existing studies have mainly examined the environmental effects of the digital economy at the national or provincial level, with limited attention to prefecture-level cities, which are important units of policy implementation. Moreover, previous research has focused largely on linear emission-reduction effects, while insufficiently exploring differences between total tourism carbon emissions and emission intensity, nonlinear effects, transmission mechanisms, and regional heterogeneity. These gaps limit a comprehensive understanding of the environmental consequences of digital transformation in tourism.

Accordingly, This study employs balanced panel data covering 282 prefecture-level cities in China from 2005 to 2023. Two-way fixed-effects and nonlinear models, together with instrumental-variable two-stage least squares (2SLS) and heterogeneity analysis, are employed to examine the effects, mechanisms, and regional differences of the digital economy on tourism carbon emissions. The study asks: (1) Does the digital economy affect total tourism carbon emissions, and does emission intensity differ? (2) Is this relationship nonlinear? (3) Does the effect vary across eastern, central, and western China? This paper contributes by extending the research scope, analytical dimensions, and empirical methods, providing evidence for differentiated digital economy and tourism emission-reduction policies [3].

2. Literature review

This paper reviews three strands of literature on the digital economy and urban tourism carbon emissions: First, tourism carbon emission measurement studies have established accounting frameworks using top-down, input-output, bottom-up, emission-factor, and IPCC-based methods—shifting from macro- to micro-analysis [4]. However, long-term, large-sample accounting at the prefecture-level city scale remains limited, while spatiotemporal analysis is fragmented and accounting standards are not yet fully consistent. Second, research on the environmental effects of the digital economy has identified three core perspectives. First, the digital economy can reduce carbon emissions through technological innovation and industrial restructuring [5]. Second, digital infrastructure investment and market expansion may generate energy-consumption rebound effects, weakening its emission-reduction benefits. Third, empirical evidence suggests a nonlinear, inverted U-shaped association between digital economy development and carbon emissions—varying notably across regions [5, 6]. Third, research on the digital economy-tourism carbon emission nexus remains relatively limited. Theoretical studies generally suggest that digitalization can facilitate the low-carbon transition of tourism, while empirical studies, mainly at the provincial level, have reported emission-reduction effects and regional heterogeneity. Using panel data from 30 Chinese provinces, this study examines how the digital economy affects carbon emissions through carbon-market synergy [7]. However, large-sample prefecture-level evidence remains scarce, and systematic analysis of transmission mechanisms, nonlinear effects, and regional disparities is still limited.

Overall, three gaps remain: first, research scale remains predominantly macro, lacking long-term, large-sample evidence at the prefecture-level city scale. Second, the mechanisms and nonlinear characteristics underlying the digital economy-tourism carbon emission relationship remain insufficiently examined. Third, perspectives focus on static linear impacts, neglecting dimensional effects and spatiotemporal disparities. This study systematically addresses these gaps.

3. Research design and model construction

3.1. Core concept definitions

The digital economy is a new economic form centered on digital technology, infrastructure, digital industrialization, and industrial digitalization. This study measures it via a comprehensive prefecture-level digital economy development index constructed using the entropy method. Tourism carbon emissions comprise direct and indirect emissions from transport, accommodation, catering, and sightseeing, emission intensity—the ratio of total emissions to tourism revenue—measures the level of green development in the tourism industry.

3.2. Theoretical foundations and research hypotheses

This study rests on three core theories. Technological innovation theory holds that digital technology optimizes tourism resource allocation and reduces energy consumption across the tourism value chain, enabling carbon reduction. The Environmental Kuznets Curve (EKC) supports a phased nonlinear relationship between the two. A regional heterogeneity perspective explains divergent digital emission reduction effects across eastern, central, and western China [3]. Four research hypotheses are: H1: The digital economy overall suppresses total tourism carbon emissions, reducing emission levels through mechanisms such as resource allocation optimization and smart management. H2: The digital economy exerts different effects over different stages on tourism carbon emission intensity. It may rise in the short term due to expanding tourism demand and higher passenger turnover frequency but decline in the medium to long term as digital technology diffuses and green transformation deepens. H3: An inverted U-shaped relationship exists between the digital economy and tourism carbon emissions: the scale-expansion effect dominates initially, while the technological emission reduction effect gradually prevails after crossing the critical threshold. H4: The emission reduction effect of the digital economy exhibits regional heterogeneity. Eastern and central regions, with better digital infrastructure and stronger governance capacity, are more likely to yield emission reduction gains, western regions, due to insufficient digital-green synergy, may experience short-term emission increases during the transition.

3.3. Data and sample processing

This study uses 2005–2023 panel data from all prefecture-level cities in China as the baseline sample. Starting from 338 prefecture-level cities, after excluding samples with severe data missingness and outliers, a balanced panel of 282 cities is obtained, with 5,396 city-year observations. Minor missing values are imputed via linear interpolation and regional mean substitution, extreme outliers are winsorized at the 1st and 99th percentiles to ensure data quality. The dependent variables—total tourism carbon emissions and emission intensity—are measured using a comprehensive proportional estimation method combined with the IPCC emission-factor method [3, 8].

3.4. Variable operationalization and measurement

Variable operationalization is shown in Table 1. Key variables are detailed below: The digital economy development index is measured using the entropy method, weighted across dimensions including internet penetration, mobile subscribers, digital industry employment, and e-commerce volume, ranging from 0.05 to 0.96. Total tourism carbon emissions were originally intended to be

calculated using the IPCC carbon emission coefficient method with energy consumption data from transport, accommodation, and catering. Sectoral energy data are unavailable at the prefecture level, so we use a comprehensive proportional estimation approach, with the core logic: "tourism carbon emissions = total societal carbon emissions $\times$ tourism activity share coefficient (R_{tourism})" [4, 8]. The formulas follow: First, urban total carbon emissions are computed from various energy consumption types:

$$\text{Carbon}_{\text{total}} = \text{Total Energy Consumption} \times 2.4567 \quad (1)$$

Where 2.4567 is the carbon emission coefficient recommended by the NDRC Energy Research Institute, and the IPCC default value of 2.6 is used for robustness checks.

$$R_{\text{tourism}} = \omega_1 \cdot \text{std}_{\text{tourism_gdp_ratio}} + \omega_2 \cdot \text{std}_{\text{tourist_density}} + \omega_3 \cdot \text{std}_{\text{hotel_density}} \quad (2)$$

$\omega_1/\omega_2/\omega_3$ denote weights determined by the entropy method, subject to the constraint $0 \leq R_{\text{tourism}} \leq 1$. Total energy consumption:

$$\text{Carbon}_{\text{tourism}} = \text{carbon}_{\text{total}} \times R_{\text{tourism}} \quad (3)$$

Tourism carbon emission intensity:

$$\text{Carbon}_{\text{intensity}} = \frac{\text{carbon}_{\text{tourism}} \times 10000}{\text{Tourism income}} \quad (4)$$

Table 1. Variable definitions and measurement table

Type	Name	Symbol	Definition
Measurement variable	Total tourism carbon emissions	carbon_tourism	Total carbon emissions generated by urban tourism activities (10,000 tons)
Dependent variable	Tourism carbon emission intensity	carbon_intensity	Total tourism carbon emissions / total tourism revenue (10,000 tons per 100 million yuan)
Core explanatory variable	Digital economy development index	digital_index	Comprehensive digital economy development index constructed by the entropy method
	Per capita GDP	ln_pergdp	Natural logarithm of regional GDP per capita
Control variable	Tertiary industry share	industry_third_ratio	Value-added of tertiary industry as a share of regional GDP
	Population size	ln_pop	Natural logarithm of the year-end resident population
	FDI share	fdi_ratio	Actually utilized foreign investment as a share of regional GDP

Table 1. (continued)

Control variable	Environmental regulation intensity	env_reg	Comprehensive environmental regulation index
	Technology investment share	tech_ratio	R&D expenditure as a share of regional GDP

3.5. Model construction

To examine the baseline effect of the digital economy on tourism carbon emissions, we employ a two-way fixed effects model:

$$Y_{it} = \alpha_0 + \alpha_1 \text{digital}_{index_{it}} + \sum \beta_k \text{Controls}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

where i denotes the city and t denotes the year, Y_{it} represents total tourism carbon emissions and emission intensity, μ_i and λ_t are city and year fixed effects, respectively, and ε_{it} is the error term.

To test the inverted U-shaped relationship between the digital economy and tourism carbon emissions, we include the squared digital economy index in the baseline model:

$$\text{carbon}_{tourism_{it}} = \beta_0 + \beta_1 \text{digital}_{index_{it}} + \beta_2 \text{digital}_{sq_{it}} \quad (6)$$

$$+ \sum \gamma_k \text{Controls}_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where $\text{digital}_{sq_{it}}$ is the squared digital economy index, other variables follow the baseline model. A significantly negative coefficient confirms the inverted U-shape. To address endogeneity, we apply IV-2SLS for robustness checks and conduct mechanism and regional heterogeneity analyses.

4. Empirical results and analysis

4.1. Descriptive statistics and correlation analysis

Table 2 show substantial cross-city variation in the digital economy and tourism carbon emissions, which is consistent with economic reality and supports the subsequent empirical analysis.

Table 2. Descriptive statistics

Symbol	mean	std	min	max	N
carbon_tourism	100.87	5.23	86.31	147.26	5396
carbon_intensity	1.80	2.43	0.02	9.50	5396
digital_index	0.07	0.08	0.05	0.96	5396
ln_per_gdp	10.48	0.74	7.91	12.49	5396
industry_third_ratio	42.41	9.74	25.00	84.80	5396
ln_pop	15.06	0.72	12.12	17.29	5396

Table 2. (continued)

fdi_ratio	0.02	0.01	0.00	0.04	5396
env_reg	0.66	0.05	0.49	0.82	5396
tech_ratio	0.02	0.01	0.00	0.04	5396

Table 3. Pearson correlation coefficient table

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) carbon_tourism	1.000	-0.444	0.512	0.368	0.328	0.387	0.112	0.220	0.115
(2) carbon_intensity	-0.444	1.000	-0.147	-0.565	-0.373	-0.427	-0.024	-0.396	-0.018
(3) digital_index	0.512	-0.147	1.000	0.261	0.236	0.114	0.195	0.130	0.222
(4) ln_pergrdp	0.368	-0.565	0.261	1.000	0.399	0.102	0.045	0.592	0.075
(5) Industry_third_ratio	0.328	-0.373	0.236	0.399	1.000	0.271	0.071	0.420	0.062
(6) ln_pop	0.387	-0.427	0.114	0.102	0.271	1.000	0.024	0.022	0.005
(7) fdi_ratio	0.112	-0.024	0.195	0.045	0.071	0.024	1.000	0.029	0.025
(8) env_reg	0.220	-0.396	0.130	0.592	0.420	0.022	0.029	1.000	0.040
(9) tech_ratio	0.115	-0.018	0.222	0.075	0.062	0.005	0.025	0.040	1.000

Table 3 shows that the digital economy reduces total tourism carbon emissions but raises emission intensity—indicating heterogeneous effects [9]. All VIFs are below 10, confirming no serious multicollinearity and validating the model specification.

4.2. Baseline regression analysis

Table 4. Baseline regression results

Variable	Model 1 : carbon_tourism (FE)	Model 2: carbon_intensity(FE)	Model 3: carbon_tourism (Nonlinear FE)
digital_index	-2.075*** (0.511)	3.183*** (0.568)	1.009 (1.187)
digital_sq	-	-	-4.391*** (1.310)
City fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
N	5396	5396	5396
R-squared	0.682	0.574	0.691
F -statistic	189.32***	127.58***	195.67***

Note: Values in parentheses are standard errors. *** p<0.01 , p<0.05 , p<0.1 .

Baseline regressions confirm the core hypotheses (Table 4). First, the digital economy has a significantly negative coefficient for total tourism carbon emissions, supporting H1. It reduces tourism carbon emissions through smart management, resource optimization, and full-chain energy control.

Second, the digital economy has a significantly positive coefficient for emission intensity at the 1% level, confirming H2's phased feature. During the sample period, the expansion of the digital economy stimulated tourism market growth, while the associated increase in energy consumption exceeded the emission reductions generated by technological improvements, thereby increasing short-term emission intensity.

Third, nonlinear results show a positive coefficient on the linear term and a significantly negative coefficient on the squared digital economy term, confirming an inverted U-shape relationship and supporting H3 (Figure 1). At the early stage, the scale-expansion effect dominates; after the threshold is crossed, the technology-driven emission-reduction effect gradually prevails.

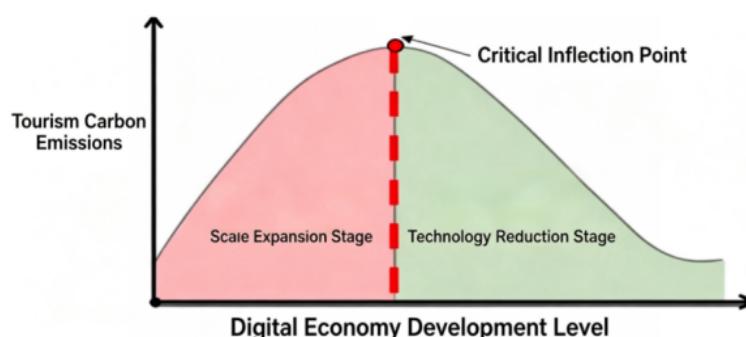


Figure 1. Inverted-U relationship between digital economy development and tourism carbon emissions

4.3. Robustness checks and endogeneity treatment

Robustness checks (variable replacement, winsorization) confirm baseline findings, with core coefficients remaining consistent in sign and statistical significance. To address reverse causality, we use the lagged digital economy index as an IV and estimate via 2SLS. The results reject weak instruments, and the negative effect remains significant—and strengthens—after endogeneity correction.

4.4. Regional heterogeneity analysis

Regional regressions confirm H4's heterogeneity hypothesis, showing a clear east-central-western gradient (Table 5).

Table 5. Regional heterogeneity

Variable	region_east	region_central	region_west
digital_index	-2.773*** (0.474)	-2.062 (1.690)	3.321* (1.811)
City fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes

Table 5. (continued)

N	1872	1568	1956
R-squared	0.713	0.658	0.632

In the eastern region, the coefficient is significantly negative—and strongest—because advanced digital infrastructure and stronger environmental governance allow technology-driven emission cuts to offset tourism's rebound effect. In the central region, the coefficient is negative but statistically insignificant, suggesting that the region is in a transitional stage where technological gains and scale expansion partially offset each other. In the western region, the coefficient is significantly positive, indicating a short-term emission-increasing effect, possibly because of relatively lagging digital development and the dominance of scale-expansion effects over technological emission reductions (See Figure 2).

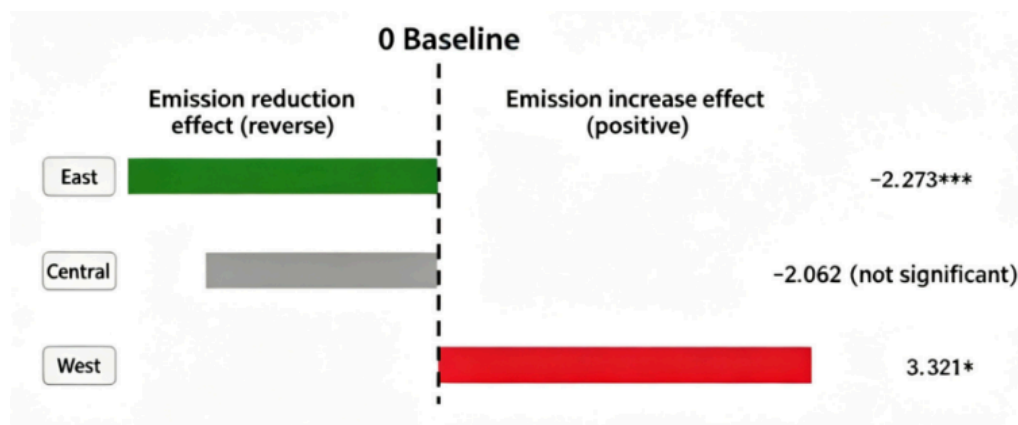


Figure 2. Regional heterogeneity analysis results

4.5. Mechanism analysis

The effects of the digital economy on tourism carbon emissions arise from the interaction of three mechanisms [10]. First, technological innovation improves energy efficiency and constitutes the main emission-reduction pathway. Big data and AI enable smart scheduling, precise energy management, and digital upgrades in transportation, accommodation, and scenic operations, thereby improving energy efficiency and reducing unnecessary emissions.

Second, market expansion generates a carbon rebound effect, contributing to short-term increases in emission intensity and the early-stage inverted U-shape relationship. The digital economy reduces information and travel costs, expands tourism demand and tourist flows, and increases energy consumption. When the resulting scale effect exceeds technology-driven energy savings, emission intensity rises.

Third, industrial integration promotes structural optimization and supports the long-term low-carbon transition. The integration of digital technologies with tourism generates low-carbon formats such as smart cultural tourism and online immersive tourism, gradually offsetting rebound effects. However, differences in digital infrastructure, technological capacity, and industrial foundations lead to regional variation in these mechanisms, resulting in a gradient pattern of "east reduction, central transition, west increase."

5. Spatial spillover effects

5.1. Spatial autocorrelation and spatial model selection

To test spatial dependence in urban tourism carbon emissions, this paper uses global Moran's I. Results show significantly positive Moran's I values at the 1% level across all years, indicating positive spatial correlation and regional agglomeration. Thus, OLS models may fail to account for spatial dependence, motivating the use of spatial econometric models.

To select the appropriate spatial model, we conduct LM, LR, Wald, and Hausman tests (Table 6). Significant LM statistics confirm spatial dependence. Both LR and Wald reject SAR and SEM specifications at the 1% level, supporting the SDM. The Hausman test rejects random effects, so we adopt a two-way fixed-effects SDM for spillover analysis.

Table 6. Spatial correlation and model selection test results

Test Item	Test Result	Conclusion
Moran's I	Significantly positive (1%)	Significant positive spatial correlation exists
LM Test	Significant (1%)	Spatial effects exist, reject conventional OLS regression
LR/Wald Test	$P < 0.01$, statistically significant	SDM cannot be simplified to SAR or SEM, adopt SDM
Hausman Test	Significant (1%)	Reject random effects specification, employ two-way fixed-effects SDM

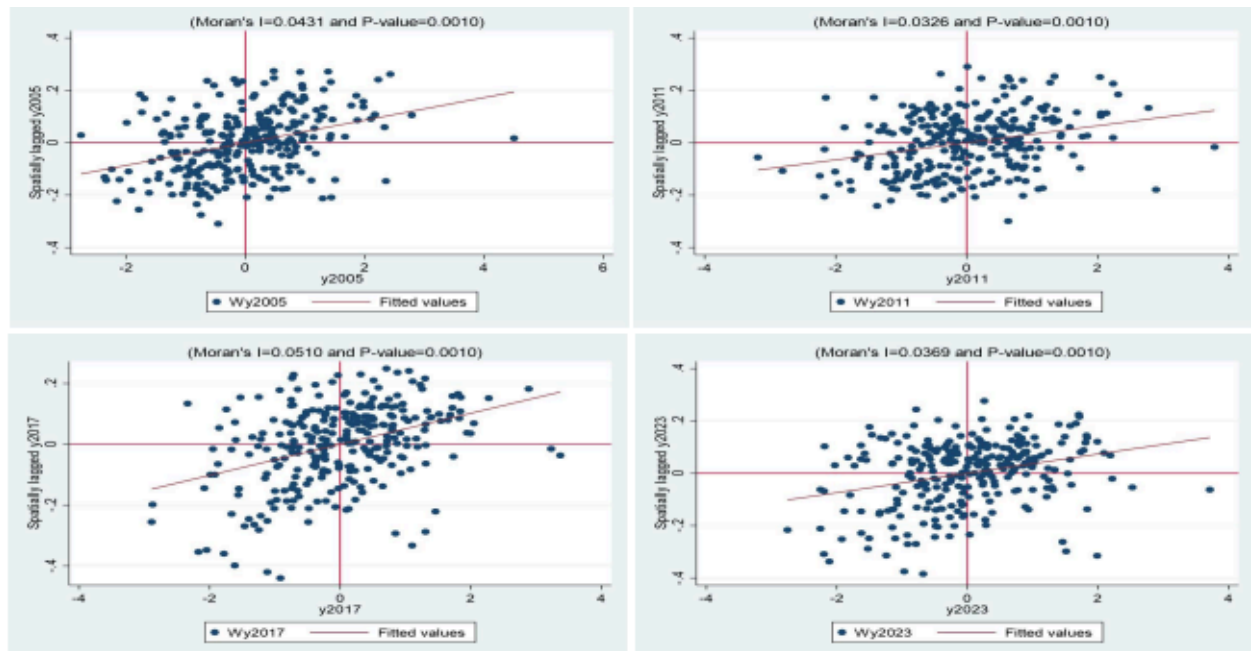


Figure 3. Local Moran scatter plot

Figure 3 shows that the local Moran's I is significant at the 1% level ($p=0.001$) in 2005, 2011, 2017, and 2023, confirming local spatial agglomeration. Most cities fall in Quadrants I (high-high) and III (low-low), indicating clustering of high- and low-emission cities, respectively. Spatial

agglomeration is strongest in 2017, while significant spatial correlation persists in the other years despite some fluctuations. The local Moran's I results confirm specific agglomeration patterns, consistent with global Moran's I, supporting the subsequent SDM analysis.

5.2. Spatial spillover effects

SDM estimates and effect decomposition reveal that the digital economy significantly cuts local tourism carbon emissions and induces negative spatial spillovers—meaning digital development in one city lowers emissions in neighboring cities.

The digital economy's low-carbon benefits transcend administrative boundaries via technology diffusion, resource linkage, and green governance coordination, forming collaborative reduction patterns and explaining the east-central-west gradient.

5.3. Decomposition of spatial effects

Following pretests, a two-way fixed-effects SDM is used, and its effects are decomposed into direct and indirect spatial effects.

(1) Direct effect: The local digital economy significantly reduces local tourism carbon emissions via technological innovation and industrial structure optimization.

(2) Indirect effect (spatial spillover): The digital economy generates positive emission-reduction spillovers to neighboring cities via technology flow, low-carbon idea diffusion, and regional coordination. Marked regional heterogeneity: the east shows the strongest bidirectional spillovers, the central has limited local reduction and weak cross-city spillovers, the west has weak digital foundations and no mature cross-regional radiation yet.

Mechanistically, energy-efficiency improvements and coordinated digital-tourism development may strengthen positive spillovers, whereas carbon rebound effects and the regional digital divide may weaken cross-regional transmission, constraining coordinated decarbonization.

Based on these spillover patterns, differentiated regional policies, low-carbon industrial chain co-construction, and cross-regional governance collaboration are needed to amplify positive spillovers and mitigate gap-driven negative impacts.

6. Conclusion

Using prefecture-level panel data, this paper examines the effects, mechanisms, and spatial spillovers of the digital economy on tourism carbon emissions. The results show that the digital economy reduces total tourism carbon emissions while increasing emission intensity in the short term, reflecting the dynamic interaction between energy-efficiency gains and tourism market expansion.

An inverted U-shaped relationship is observed: the scale-expansion effect dominates at the early stage, while technology-driven emission reduction becomes stronger after the threshold is crossed. Significant regional heterogeneity is also identified: the eastern region shows the strongest emission-reduction effect, the central region has a weaker effect, and the western region exhibits a short-term emission-increasing effect. Three main mechanisms underlie these effects: energy-efficiency improvement through technological innovation, carbon rebound from market expansion, and structural upgrading through industrial integration. Spatial analysis further shows that digital development generates positive emission-reduction spillovers across cities.

Based on these findings, three policy directions are proposed: (1) Tiered regional policies: The eastern region should further leverage its digital advantages for emission reduction, the central region should strengthen low-carbon standards for new tourism projects, and the western region should promote low-cost digital technologies in ecotourism and strengthen interregional cooperation. (2) Full-chain digital low-carbon applications: Digital technologies should be integrated into transportation, accommodation, scenic operations, and tourism consumption, while carbon-inclusion programs can encourage green travel and low-carbon consumption. (3) Institutional support: Policymakers should strengthen top-level planning, fiscal incentives, carbon monitoring, R&D support, and cross-departmental governance to facilitate the low-carbon transition of tourism.

This study has two limitations. First, prefecture-level tourism carbon emissions are estimated using a proportional method, leading to limited accuracy for sub-sector measurement. Second, cross-regional spatial spillovers are not sufficiently explored. Future work shall refine carbon-emission estimation, adopt spatial econometric models to unpack regional joint-reduction rules, and provide empirical support for cross-regional collaborative low-carbon governance of cultural-tourism sectors.

References

- [1] Liu, Z., Yang, Y., Liu, A. Y., et al. (2025). Digital economy, virtual network embeddedness and tourism economic linkage. *Tourism Tribune*, 40(10), 98–116. DOI: 10.19765/j.cnki.1002-5006.2025.00.011.
- [2] Li, X. F., & Zhu, J. L. (2026). Impact of energy policy on green total factor productivity: A quasi-natural experiment based on energy use right trading pilot policy. *Ecological Economy*, 42(2), 144–153. https://kns.cnki.net/kcms2/article/abstract?v=pX0ZfcSLBkU8SrcWL5AqsjHvU4UCXv962-fiJ5LLfis_rKxTeWtgDiAOX09H0quNGL9qvcG3d1m-sTQPTKqgy0YQ5Os2dhid7qEEDiCUdQ3S-VCNj0ws3KH6J5JOW6jsmLqS328B4GsRqYLPGIOcWK2l2pVboG9aKEv5nGWyaHkVKvpfD3to-Q=&uniplatform=NZKPT&language=CHS
- [3] Wang, K., Zhang, S. W., Gan, C., et al. (2020). Spatial network structure and its effects of carbon emission efficiency of China's tourism industry. *Scientia Geographica Sinica*, 40(3), 344–353. DOI: 10.13249/j.cnki.sgs.2020.03.002.
- [4] Zhong, Y. D., Shi, S. Y., Li, S. H., et al. (2014). Construction and empirical study on carbon emission measurement framework of China's tourism industry. *China Population, Resources and Environment*, 24(1), 78–86. <https://link.cnki.net/urlid/37.1196.N.20140110.2127.012>
- [5] Ling, B., Tianran, G., Wei, X., et al. (2023). Effects of digital economy on carbon emission intensity in Chinese cities: A life-cycle theory and the application of non-linear spatial panel smooth transition threshold model. *Energy Policy*, 183. DOI: 10.1016/J.ENPOL.2023.113792.
- [6] Jiang, L., Hu, J. L., & Zhang, Z. L. (2025). Carbon reduction and efficiency improvement effect of digital economy and its realization paths: Empirical evidence from 88 countries. *China Population, Resources and Environment*, 35(6), 1-15. https://kns.cnki.net/kcms2/article/abstract?v=pX0ZfcSLBkUkAsPezlmbiRvzt599kHsK9gD0AGQqiSAYjQOll0KvgdJW00uwn307-BbApylim9edVwU22FtFixZ4yyPeqQZhlYEBU_WtGI32tHcQb9Iy_u2bU2opKpFWKwD4Xj0uE36_m8MbQ7QzAhY7k1UUzO6yY9aCydkjgRsviYi8tykB9A=&uniplatform=NZKPT&language=CHS
- [7] Qiao, H. Y., & Wu, S. M. (2025). Impact of digital economy on carbon emissions from the perspective of carbon trading market synergy. *Ecological Economy*, 41(9), 41-51. https://kns.cnki.net/kcms2/article/abstract?v=pX0ZfcSLBkVR0JlCok0vQKfkddKYsvBVkzoiK4rjAQKGHWdyGWnzLJ2R_zeHMFHvSQWoSgy8Nc3Ractj4IKYvDtMgntjsDImLAWFLsvrjgsfCGGerY9HTYbiZjggaN9uETvjXr3wQJjPrLVxLvOvw16GeCZqA9pCrbxhtbBgT3dYseJYjDtSpA=&uniplatform=NZKPT&language=CHS
- [8] Huang, M. Z., & Huang, X. K. (2022). Measurement and spatial differentiation of carbon emission decoupling effect of tourism industry in Yangtze River Delta urban agglomeration. *Journal of Central South University of Forestry & Technology*, 42(5), 170-180. DOI: 10.14067/j.cnki.1673-923x.2022.05.019.
- [9] Li, X. (2015). Research on carbon emission accounting and optimization of urban tourism system: A case study of Kaifeng City. Henan University. <https://kns.cnki.net/kcms2/article/abstract?>

v=pX0ZfcSLBkXKoNbmrD80QWsrdbwXgS4IAmxsAAZS4SXG7cd4gkWQjbIGOl6rGL0babv_k5n7c3ORiALW
WpJtM6BXmC3kGIVNDfeADiPRff_RbaTl sygjNy0JPd2Wf3-0pUf5wTQhWhZYdiISU0-p-
dqF6evpC1WhP3u5cDxAwsB1ggadqgQG1NY6FpxyLPjR&uniplatform=NZKPT&language=CHS

- [10] Li, Y., Zheng, G., & Dong, H. A. (2025). Measurement and driving factors of tourism transportation carbon emissions in Jiangsu Province based on LMDI decomposition. *Energy Conservation*, 44(11), 110-113.
<https://link.cnki.net/urlid/21.1115.TK.20251120.1346.046>