Digital Technology on Carbon Emission Intensity of China's Tourism Sector Impact studies

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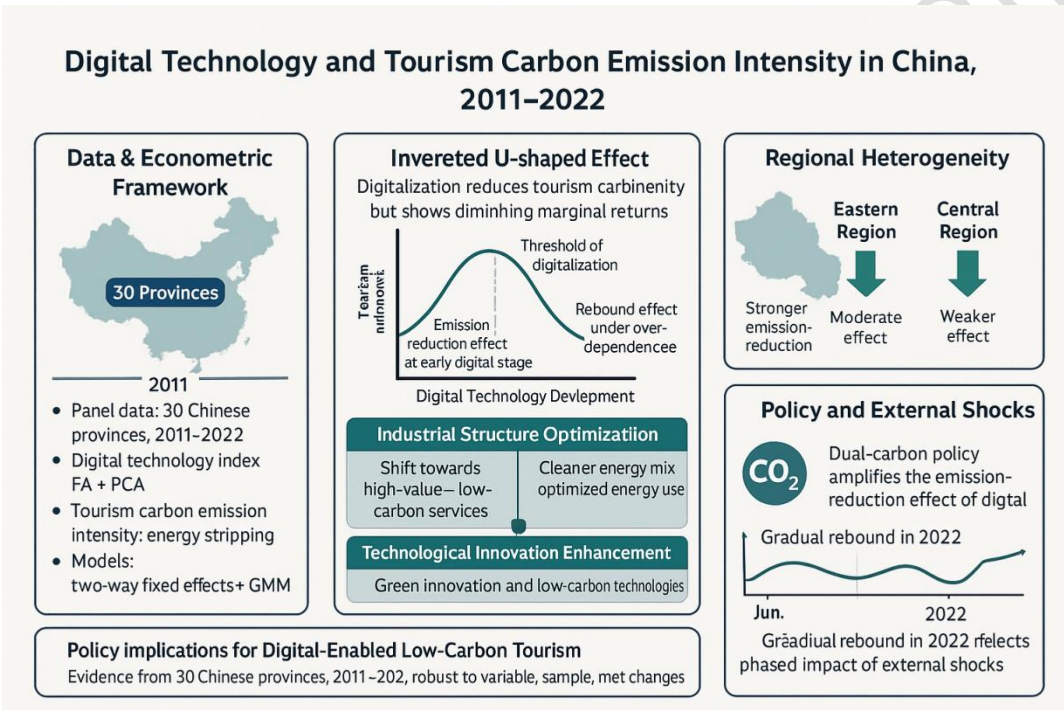


Abstract: Under China's "dual-carbon" targets, the tourism industry's green transformation increasingly depends on deep integration of digital technology. Using panel data from 30 Chinese provinces (2011–2022), this study constructs a tourism carbon emission intensity dataset with an energy-stripping method and develops a multidimensional digital technology index via factor analysis. Two-way fixed-effects and system GMM models are employed to estimate the impact of digital technology on tourism carbon intensity, while nonlinear specifications test for turning-point effects. Regional heterogeneity is examined through cluster-based quantile regressions, and a structural equation model verifies three transmission mechanisms: industrial structure upgrading,

energy-efficiency improvement, and innovation enhancement. Multiple robustness checks (lagged regressions, placebo tests, Monte Carlo simulation, counterfactual analysis) confirm result reliability. The findings show that digital technology significantly reduces tourism carbon emission intensity and exhibits an inverted U-shaped relationship, with a strengthened decarbonization effect after China's "dual-carbon" policy. All three mediating channels are significant, and the effects vary across regional development levels and carbon-intensity quantiles. Provides sector-specific evidence of digital-driven decarbonization and offers policy implications for promoting smart, low-carbon tourism in developing economies.

Keywords: digital technology; tourism industry; carbon emission intensity; nonlinear relationship; mediating mechanisms

1. Introduction and Literature Review

Rapid advances in cloud computing, big data, the Internet of Things (IoT), artificial intelligence (AI), and 5G communication have accelerated digital transformation across industries, while energy-intensive development has increased environmental pressures. China has committed to peak carbon emissions by 2030 and achieve carbon neutrality by 2060 at the 75th United Nations General Assembly. Under these "dual-carbon" targets, sector-specific low-carbon transition pathways are increasingly required.

Tourism is a key service sector but also an important source of carbon emissions due to its dependence on transportation, accommodation, and supporting infrastructure. With fast digitalization and tighter climate constraints, it is necessary to clarify how digital technology affects tourism carbon emission intensity. Existing studies mainly address tourism carbon measurement, digitalization-related mitigation mechanisms, and regional heterogeneity.

1.1 Tourism carbon emission measurement

Tourism carbon emission intensity (carbon emissions per unit of tourism output) is widely used to evaluate tourism carbon efficiency (Sun, 2023). However, measurement remains challenging due to fragmented service chains and heterogeneous activity boundaries, and large spatial differences have been reported across destinations (Li et al., 2024).

Two accounting approaches are common. Top-down methods allocate emissions using energy balance sheets and input–output tables (Kelly et al., 2007), while bottom-up methods aggregate emissions from transport, accommodation, and sightseeing (Dong et al., 2023). In China, the lack of a unified tourism carbon accounting system often leads to boundary inconsistencies and indirect estimation.

Tourism transport has long been emphasized because it contributes more than 70% of global tourism-related emissions, with aviation dominating this share (Bach, 1996; Becken, 2002; World Tourism Organization, 2009; Lenzen et al., 2018). In China, tourism transportation accounted for nearly 90% of tourism emissions during 2000–2013 (Liu et al., 2019). Subsequent studies examined spatial–temporal evolution and drivers using the Theil index, exploratory spatial data analysis, STIRPAT models, LMDI decomposition, and efficiency measures (e.g., SBM and Super-SBM), documenting significant regional disparities (Huang, 2019; Huang et al., 2019; Shao, 2020; Yao et al., 2021; Cheng et al., 2023). Tourism scale and energy use generally increase emissions, while lower energy intensity and higher tourism productivity mitigate emission growth (Huang et al., 2019; Yao et al., 2021). Nevertheless, most studies focus on internal drivers, and the role of external drivers—especially digital technology—remains insufficiently addressed.

1.2 Digital technology and emission-reduction mechanisms

Digital technology is widely viewed as a driver of low-carbon transition by improving efficiency, optimizing resource allocation, and enabling real-time monitoring (Gao et al., 2022; Dogan & Pata, 2022; Zhang et al., 2021), thereby supporting carbon neutrality targets (Zhong, 2023). In tourism, digital infrastructure and smart services are associated with service upgrading and higher-quality development (Zhang & Shang, 2022), and evidence suggests that digital economy development improves tourism carbon emission efficiency in China (Su et al., 2023).

At the macro level, platforms and data-driven governance can support tourism growth and service upgrading (Kumar, 2020; Cheng, 2023; Yang, 2023; Wu et al., 2023). At the micro level, digitalization can enhance coordination and factor allocation, increasing total-factor carbon productivity (Bai et al., 2021). Firm-level studies further report improvements in carbon performance following digital transformation (Li, 2024; Cai et al., 2024; Wang et al., 2024; Fang et al., 2025). Cross-sector evidence from intelligent modelling and smart process control also shows that digital technologies reduce energy use and emissions (Gao et al., 2022; Zhang et al., 2021; Cai et al., 2024a; Cai et al., 2024b; Cai et al., 2025; Ramachandran et al., 2025; Pydi et al., 2025a; Sivasundar et al., 2025; Vijayakumar, 2025; Pydi et al., 2025b), supporting their application to tourism.

Importantly, the digital–carbon relationship may be non-linear. Several studies identify an inverted U-shaped relationship between digital economy development and carbon emissions (Xu et al., 2025; Zhou et al., 2025), suggesting that early-stage infrastructure expansion may raise energy demand, while later-stage efficiency gains and innovation dominate (Sun & Zhou, 2022; Zeng, 2025).

1.3 Regional heterogeneity and research gaps

Tourism carbon emission intensity varies markedly across China due to differences in development levels, resource endowments, and industrial structure. Evidence from the Yangtze River Economic Belt shows upstream–downstream differences and convergence trends (Huang, 2019). Spatial analyses reveal high-intensity clusters in eastern coastal provinces and lower-intensity clusters in western regions (Yao et al., 2021), while efficiency studies indicate higher tourism carbon efficiency in more developed regions (Cheng et al., 2023).

The mitigation effects of digitalization also differ across regions. Empirical studies suggest stronger carbon-reducing impacts where digital readiness is higher and weaker effects in less developed areas (Sun & Zhou, 2022; Zeng, 2025). However, tourism studies often provide limited mechanism-based explanations for heterogeneous effects, and much of the non-linear digital–emission literature remains at aggregate or multi-sector levels.

1.4 Contribution and positioning of this study

This study addresses these gaps by developing a tourism-specific framework that constructs a refined measure of tourism carbon emission intensity, tests the non-linear impact of digital technology, identifies multiple transmission mechanisms, and examines regional heterogeneity across China. By integrating the Technology Acceptance Model and Resource Allocation Theory, it provides sector-level evidence on how digital transformation supports low-carbon tourism under China's dual-carbon targets.

2. Theoretical Analysis and Research Hypotheses

To explain how digital technology affects tourism carbon emission intensity, this study integrates the Technology Acceptance Model (TAM) and Resource Allocation Theory (RAT). TAM emphasizes micro-level adoption driven by perceived usefulness and ease of use (Davis, 1989). In tourism, digital applications such as online booking, e-ticketing, and smart management systems improve operational efficiency and service quality.

RAT explains how digitalization reshapes the allocation of capital, labor, and energy across sectors, redirecting resources toward energy-saving equipment and intelligent systems. In tourism, digital infrastructure supports energy optimization, industrial upgrading, and green innovation. Together, TAM explains adoption motivation, while RAT clarifies how adoption translates into resource reallocation and emission reduction, forming the basis for the following hypotheses.

2.1 Efficiency improvement mechanism

Digital technology can reduce tourism carbon emission intensity by improving energy efficiency and resource utilization. Digital tools such as IoT sensors, big data analytics, and intelligent management systems enable real-time monitoring and optimization of energy use in tourism facilities. Online booking and e-ticketing further reduce material inputs and operational costs, thereby lowering emissions per unit of output.

Hypothesis 1 (H1). Digital technology development is negatively associated with tourism carbon emission intensity.

This mechanism is consistent with RAT and supported by studies showing that digital penetration improves efficiency and reduces carbon intensity through better resource allocation (Sun & Zhou, 2022).

2.2 Industrial structure upgrading mechanism

Digital technology promotes industrial structure upgrading in tourism by improving the efficiency of information, capital, and logistics matching. It facilitates a shift from high-carbon subsectors toward low-carbon and high value-added activities, such as smart tourism and digital services, thereby reducing overall carbon emission intensity.

Hypothesis 2 (H2). Digital technology reduces tourism carbon emission intensity by promoting industrial structure upgrading.

Smart tourism platforms and AI-based management systems further enhance energy efficiency and support this structural transition. Empirical evidence confirms that digital applications significantly reduce energy intensity and emissions across tourism facilities (Li et al., 2024).

2.3 Innovation stimulation mechanism

Digitalization stimulates green innovation in tourism by supporting new products, services, and management models. Digital tools enable energy-saving solutions, carbon monitoring, and innovative business models such as virtual tourism and sharing platforms, which reduce physical resource consumption.

Hypothesis 3 (H3). Digital technology reduces tourism carbon emission intensity by enhancing green innovation capacity.

Firm-level studies show that digital transformation significantly promotes green innovation and improves environmental performance, particularly in tourism enterprises facing competitive and regulatory pressures (Fang et al., 2025).

2.4 Non-linear mechanism

The impact of digital technology on tourism carbon emission intensity may be non-linear. At early stages, infrastructure expansion may increase energy demand, while efficiency gains, industrial upgrading, and innovation dominate beyond a threshold. At higher levels, diminishing marginal returns and rebound effects may weaken emission-reduction benefits.

Hypothesis 4 (H4). There exists an inverted U-shaped relationship between digital technology development and tourism carbon emission intensity.

Recent empirical studies document similar non-linear dynamics between digital economy development and carbon emissions (Xu et al., 2025; Zhou et al., 2025). This study extends these insights to the tourism sector.

Figure 1 presents the integrated theoretical framework based on TAM and RAT. Digital technology affects tourism carbon emission intensity through three main channels—efficiency improvement, industrial structure upgrading, and innovation stimulation—while exhibiting potential non-linear effects. These hypotheses are empirically tested in the subsequent sections.

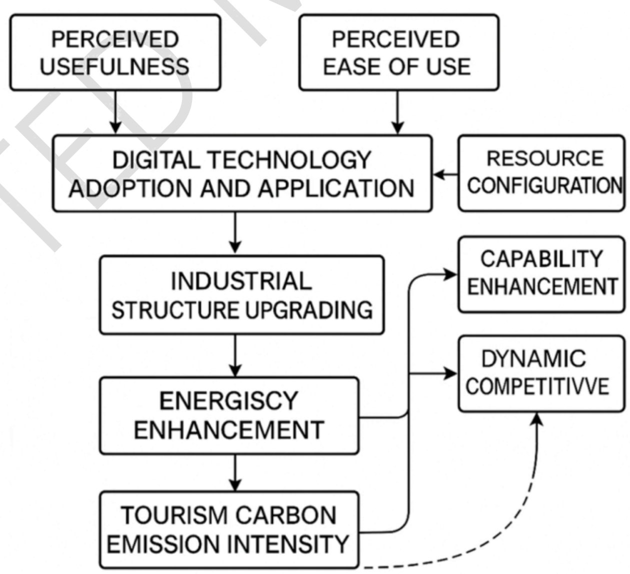


Fig. 1 Systematic analysis framework based on TAM model and RAT theory

3.Data sources and modeling

3.1 Data sources and carbon emissions stripping methods

This study employs a balanced panel of 30 provincial-level regions in mainland China from 2011 to 2022. Tibet Autonomous Region, Hong Kong, Macao, and Taiwan are excluded to ensure data consistency and comparability. Tibet is omitted because its tourism sector is highly specialized (e.g., religious pilgrimage and eco-tourism), exhibits atypical carbon emission patterns, and lacks complete tourism-related energy statistics over the study period. Moreover, Tibet's digital infrastructure and technology adoption lag substantially behind other provinces, and its distinctive policy environment may generate leverage effects in regression estimation.

Hong Kong, Macao, and Taiwan are excluded because they are not fully integrated into the mainland provincial statistical system. Differences in statistical definitions, data availability, and institutional contexts—together with their exceptionally high levels of digital penetration—would introduce heterogeneity that could bias parameter estimates. As a result, the empirical analysis focuses on mainland provinces with comparable economic structures, digital development trajectories, and policy frameworks.

Potential bias from these exclusions is limited. The omitted regions account for a small share of national population and tourism activity, and the use of two-way fixed effects further absorbs time-invariant regional characteristics and nationwide shocks. Nevertheless, the results do not capture high-altitude tourism dynamics in Tibet or highly urbanized digital ecosystems such as Hong Kong, which is acknowledged as a limitation.

The source of basic data consists of two main aspects:

（1）Primary data on carbon emissions from tourism at the provincial level. Raw data on carbon emissions from tourism at the provincial level are obtained from provincial statistical yearbooks and official.

（2）Data on 12 types of end-use energy consumption in tourism-related industries. The consumption of 12 end-use energy sources (raw coal, coal, coke, crude oil, gasoline, kerosene, diesel fuel, fuel oil,

In order to estimate the direct energy consumption of China's tourism industry, we used the industry association weight coefficient method for energy consumption stripping:

Industry association coefficient (): Firstly, the industry association coefficients are calculated based on the proportion of the output value of tourism-related industries (transportation, storage and postal services, wholesale and retail.

The coefficient matrix is used to deconstruct the end-use energy consumption of the tertiary industry in China, and obtain the baseline value of energy consumption of tourism-related industries.

Terminal energy decomposition (E_{ij}): the terminal energy consumption of each tertiary industry is assigned to tourism-related sub-industries using the Pit coefficient.

Tourism Development Coefficient (R_t): Calculate tourism-specific adjustment coefficients, i.e. the ratio of tourism revenue to tertiary GDP for each province and year.

Tourism Energy Consumption (E_t): the product of R_t, P_{it} and E_{ij} yields the estimated direct energy use of the tourism industry in each province, as shown in equation (1):

$$E_{\mathrm{t}} = R_t . \sum_i (p_{it} . E_{ij}) \tag{1}$$

Specific explanation:

E_{t} is the total energy consumption of the tourism industry in the province,

R_t is the coefficient of tourism development,

P_{it} is the share of tourism-related industries in the tertiary industry,

E_{ij} is the sectoral end-use energy consumption by energy type.

Using these energy consumption estimates, we subsequently calculated carbon emissions by applying fuel-specific emission factors and national CO2 conversion factors in accordance with the IPCC guidelines, as shown in Equation (2)(3):

$$C_t = \sum_j (E_{ij} . f_j . k) \tag{2}$$

$$C_p = \frac{C_t}{Tourism\,\mathrm{Re}\,venue_t} \tag{3}$$

where C_t is the overall carbon emissions and C_p is the carbon intensity (in tons per million dollars of tourism revenue).

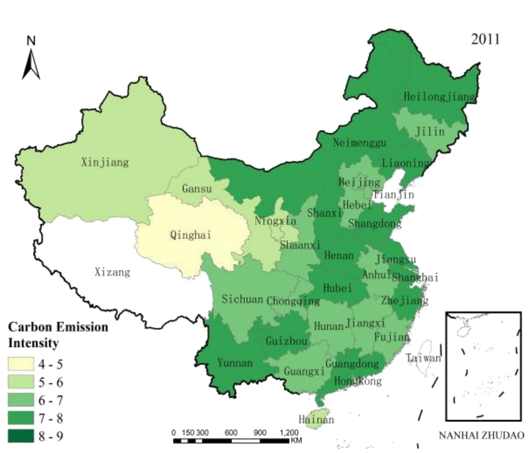
(3)Robustness analysis of the energy stripping method. This suggests that the energy stripping approach used in this study is methodologically robust and relatively insensitive to modest changes in the base.

(4) To address potential concerns regarding the robustness and credibility of the tourism carbon emissions estimates derived from the energy stripping method, this study undertook a multi-pronged reinforcement strategy.

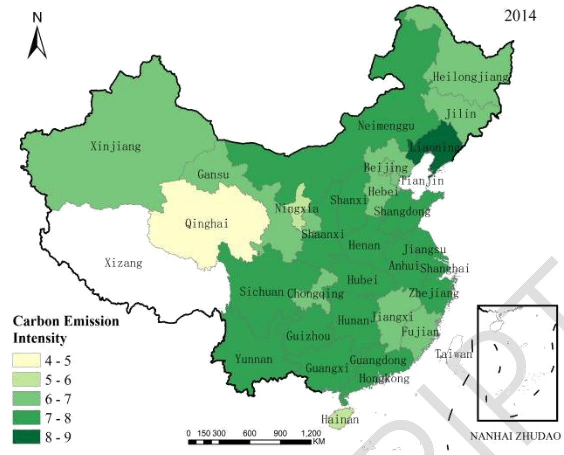
For transparency, the values and data sources of the tourism energy decomposition parameters (α, β, γ) and sector-specific emission factors used in equations (1)–(3) are reported in Appendix A.

3.2 Horizontal spatial disaggregation of carbon emission intensity in China's tourism industry

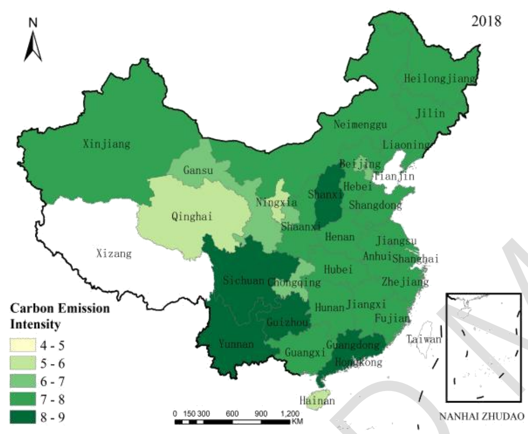
From the horizontal spatial stratification of carbon emission intensity of China's tourism industry, it can be seen that the overall carbon emission intensity of China's tourism industry decreases from 2011 to 2022, and the provinces with lower values of carbon emission intensity that remain at low levels include Qinghai, Gansu, Ningxia, Xinjiang, Jilin, Beijing, Hebei, and Fujian.



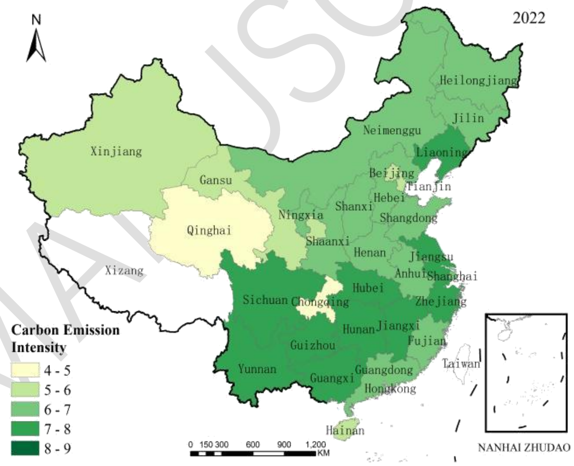
(a)Spatial Quantile Map of Carbon Emission Intensity in China's Tourism



(b)Spatial Quantile Map of Carbon Emission Intensity in China's Tourism Industry (2014)



(c) Spatial Quantile Map of Carbon Emission Intensity in China's Tourism Industry (2018)

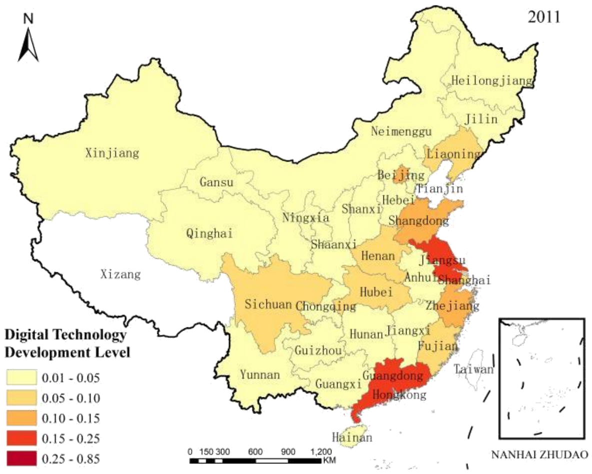


(d) Spatial Quantile Map of Carbon Emission Intensity in China's Tourism Industry (2022)

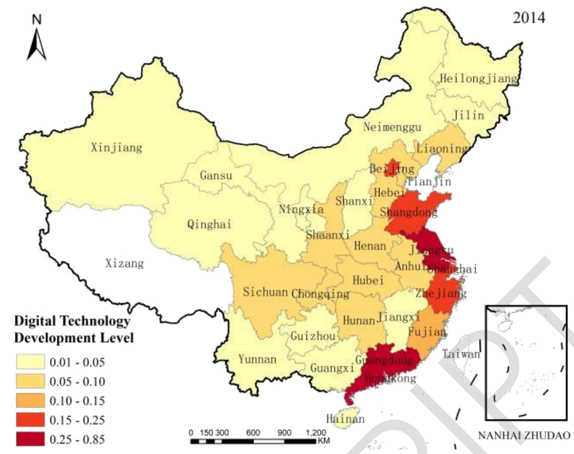
Fig 2. Spatiotemporal Distribution of Carbon Emission Intensity in China's Tourism Industry

This map is based on the standard map No. GS [2024] 0650 downloaded from the standard map service website of the Map Technical Review Center of the Ministry of Natural Resources, with no modifications to the base map. The bottom map is the same.

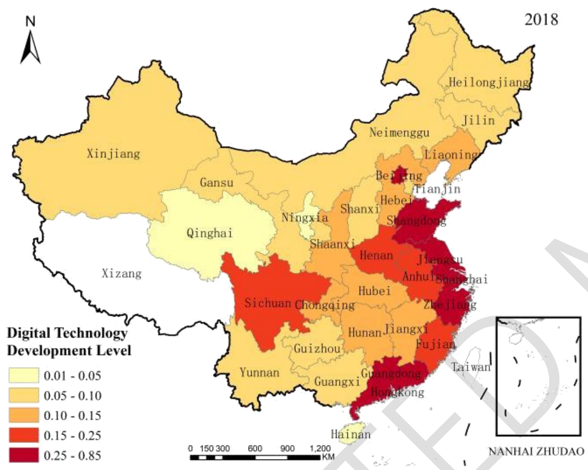
Meanwhile, the spatial quantile map of the development level of digital technology in China's tourism industry shows that digital technology in China's tourism industry has developed rapidly from 2011 to the present, and the new crown virus has promoted the use of digital technology in the tourism industry to promote the transformation of the industrial structure and development.



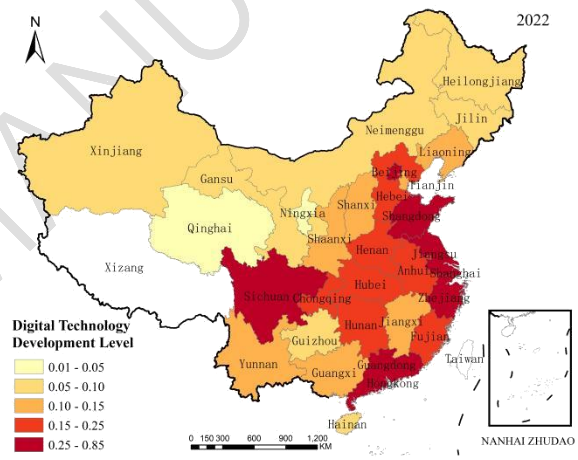
(a)Spatial Quantile Map of Digital Technology Development Level in China (2011)



(b) Spatial Quantile Map of Digital Technology Development Level in China (2014)



(c)Spatial Quantile Map of Digital Technology Development Level in China (2018)



(d) Spatial Quantile Map of Digital Technology Development Level in China (2022)

Fig 3. Spatiotemporal Distribution of Digital Technology Development Level in China's Tourism Industry

3.3 Construction of Digital Technology Indicator System

3.3.1 FA–PCA-Based Digital Technology Indicator System for Tourism

Factor analysis (FA) and principal component analysis (PCA) were used to construct the digital technology indicator system. All indicators were standardized to ensure comparability. Factor analysis (FA) was used to identify potential factors by grouping related indicators into subsystem layers such as "digital technology infrastructure construction", "digital technology application penetration" and "digital technology benefits".

To enhance conceptual alignment, we critically reviewed and removed any indicators deemed insufficiently relevant to the tourism context. The revised indicator system retains only those dimensions that contribute meaningfully to capturing digital infrastructure, application breadth, and spillover benefits to tourism. Each retained indicator is explicitly mapped to its theoretical contribution.

Table 1 Digital technology indicator system

Target Layer	Subsystem layer	Indicator layer	Unit	Attribute
Digital technology level	Digital technology infrastructure Facility Construction	Number of 5G base stations and coverage rate (%)	Number of Base Stations/Coverage Rate (%)	+
		Market Penetration Rate	Market share (%)	+
		Data Center Size and Energy Efficiency	Number of Data Centers/Energy Efficiency (kWh/GB)	+
		Internet Access Rate (Fixed & Mobile Broadband)	(Number of users per 100 people)	+
		Internet of Things Device Penetration Rate	(Number of devices per 1,000 people)	+
		Smart device penetration rate (smartphones, smart home devices, etc.)	Number of users (per 100 people)	+
		Penetration rate of electronic payment systems	Frequency of transactions (per month)	+
	Digital technology specific Application penetration rate	Wireless Communication Technology Coverage	Coverage area (%)	+
		High Performance Computing Platform Construction	Investment (RMB billion)	+
		Data Privacy Protection Technology Application	Technology Adoption Rate (%)	+
		Market Penetration of Cloud Computing Services	Market share (%)	+
		Intelligent Transportation System Construction	Investment (RMB billion)	+
		Application and Popularization of Intelligent Manufacturing Technology	Equipment Penetration Rate (%)	+
		Application rate of artificial intelligence (AI) in various industries	Application coverage rate (%)	+
		Application of Intelligent	Proportion of users	+

	Digital Technology Generation Benefits	Education Technology	(%)	
		Intelligent Retail System Applications	Market coverage (%)	+
		Data Mining and Analysis Technology Application	Enterprise Adoption Rate (%)	+
		5G Network Access Capacity	Number of Access Users (million)	+
		High-speed Internet Infrastructure Construction	Investment amount (RMB billion)	+

The composite index is constructed using an objective entropy–TOPSIS procedure to minimize subjective weighting.

$$e_j = -k\sum_{i=1}^{N} p_{ij} \ln p_{ij}\ ,\ \ k = (\ln N)^{-1},$$

and its divergence $d_j = 1 - e_j$. The entropy weight is then

$$\omega_j = \frac{d_j}{\sum_{m=1}^{M} d_m},$$

assigning greater weight to indicators with higher cross-provincial discrimination.

$$S_i^+ = \sqrt{\sum_j (\omega_j z_{ij} - A_j^+)^2}\ ,\ \ S_i^- = \sqrt{\sum_j (\omega_j z_{ij} - A_j^-)^2}$$

and the closeness coefficient is.

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \in [0,1],$$

which serves as the province-level digital technology score. Factor analysis/PCA is used diagnostically to assess dimensional coherence and redundancy (e.g., loading structure, variance capture) rather than to set weights; entropy–TOPSIS supplies the final, data-driven weights and aggregation.

3.3.2 Index validity and robustness.

Multiple checks support the validity and robustness of the digital technology index. The index rankings align well with provinces widely recognized as digital leaders, while lower-ranked provinces are typically less developed western regions. In addition, correlation tests with alternative digital proxies and sensitivity analyses using modified indicator sets confirm that the index and subsequent regression results are stable.

3.4 Data Modeling

The paper selected the digital technology sample data of China's 30 provincial panels during the period of 2011-2022 and measured the level of digital technology using the entropy weight TOPSIS method.

Table 2. Descriptive statistics results of all empirical test variables

VarName	Obs	Mean	SD	Min	Median	Median
carbon	360	7.014	0.817	4.094	7.171	8.804
digital	0.130	0.130	0.126	0.126	0.019	0.827
GDP	360	9.905	0.870	7.421	9.959	11.768
gov	360	0.247	0.102	0.107	0.224	0.224
tech	360	0.005	0.003	0.003	0.004	0.004
edu	360	0.039	0.014	0.021	0.034	0.091
open	360	0.017	0.025	0.000	0.007	0.152
struc	360	0.480	0.480	0.297	0.475	0.839

The study systematically implemented multidimensional statistical diagnostic procedures prior to modeling. Firstly, Pearson's bivariate correlation analysis (Pearson's r) was carried out to initially explore the characteristics of the association between variables. It can be seen that the core explanatory variable, Digital, is statistically significantly and positively associated with Carbon, a finding that is directionally different from theoretical expectations.

Table 3 Correlation coefficient matrix test results

	carbon	digital	GDP	gov	tech	edu	open
carbon	1.000						
digital	0.257***	1.000					
GDP	0.640***	0.725***	1.000				
gov	-0.486***	-0.463***	-0.818***	1.000			
tech	0.003	0.483***	0.186***	-0.095*	1.000		
edu	-0.326***	-0.450***	-0.714***	0.887***	-0.139***	1.000	
open	0.048	0.398***	0.300***	-0.357***	0.508***	-0.413***	1.000

*** p<0.01, ** p<0.05, * p<0.1

In order to ensure that the various types of indicators analyzed cover different dimensions (such as government intervention, technological expenditure, industrial structure, etc.), and there is no overlap in the theoretical logic of each other, the study adopts.

Table 4 Covariance test results of selected indicators

	VIF	1/VIF
gov	7.951	126
GDP	6.168	0.162
edu	5.002	0.2
digital	3.304	0.303
tech	1.706	0.586
open	1.641	0.609
Mean VIF	4.295	

Under the econometric theoretical framework of panel data modeling, the applicability of models needs to be systematically examined in terms of the structural suitability of mixed regression models, fixed effects models and random effects models.

Table 5 Hausman test and F-test results

Hausman test			F test		
chi2 statistic	p value	result	chi2 statistic	p value	result
25.55	0.000	reject	12.66	0.000	reject

According to the results of Hausman test, the fixed effect model was chosen due to the existence of the test probability 0<P<0.05, Hausman test as well as the F-test result statistic were significant to reject the original hypothesis.

3.4.1 Two-way fixed effects model setting and diagnosis

Model structure: a panel two-way fixed-effects model is used to control individual heterogeneity (γ_i) and time trend (λ_t), and the specific calculation process is shown in equation (4).

The regression result equation is:.

$$carbon_{it} = \alpha_0 + \beta_1 digital_{it} + \beta_{2-6} controls_{it} + \gamma_i + \lambda_t + \varepsilon_{it} \tag{4}$$

Controls: set of control variables (including GDP, gov, tech and other variables)

α_0 : constant term

β_{1-6} : Coefficients of each explanatory variable

γ_i : individual fixed effects

λ_t : time fixed effect

ε_{it} : random perturbation term

The within-group R^2 of models (1) to (3) improves from 0.580 to 0.646, indicating that the gradual inclusion of control variables enhances the explanatory power of the model to capture 64.6% of the sources of variation in carbon emission intensity. Meanwhile, the F-statistic was significant (P<0.01), verifying the overall validity of the model.

The coefficients of digital technology in the three models are negative and highly significant (P<0.01), specifically -1.908 (model 1), -2.607 (model 2), -2.469 (model 3), indicating that for every unit of improvement in digital technology, the intensity of carbon emission will be reduced by 1.9 units on average.

Table 6 Analysis of benchmark regression results of fixed-effects model

VARIABLES	(1) carbon	(2) carbon	(3) carbon
digital	-1.908***	-2.607***	-2.469***
	(-25.40)	(-16.46)	(-8.82)
GDP		1.136***	1.201***
		(10.65)	(14.11)
gov		2.713***	1.396
		(3.89)	(1.43)
tech		36.795***	33.502***
		(4.87)	(4.10)
edu			14.797***
			(4.44)
open			2.934
			(0.94)
Constant	6.875***	-5.486***	-6.433***
	(445.42)	(-4.48)	(-6.08)
Observations	360	360	360
R-squared	0.580	0.638	0.646
Number of groups	30	30	30

area	YES	YES	YES
year	YES	YES	YES

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

3.4.2 GMM model setting and diagnosis

To address potential bidirectional causality and other endogeneity concerns between digital technology development and tourism carbon emission intensity, a dynamic panel data model is estimated using the System GMM approach. Tourism carbon emission intensity is treated as a dynamic process, as past emission performance may influence current outcomes through persistence effects.

Endogeneity may arise from three main sources. First, reverse causality may exist because digital technology can reduce carbon emission intensity, while regions with higher emissions may simultaneously increase investment in digital technologies to improve energy efficiency. Second, omitted variables, such as economic development level, industrial structure, and environmental regulation intensity, may jointly affect both digitalization and carbon emissions. Third, measurement error may be present because digital technology development is captured by a composite index. These issues can lead to correlation between explanatory variables and the error term, biasing conventional fixed-effects estimates.

Accordingly, this study adopts a two-step System GMM estimator. Lagged values of endogenous variables are used as internal instruments, while external instruments are constructed based on historical and geographic characteristics to strengthen identification.

3.4.3 Instrument selection and validity tests

External instrumental variables include historical communication infrastructure (e.g., landline telephone penetration in the 1980s and historical postal network density), which reflect early information connectivity and are strongly correlated with contemporary digital development but unlikely to directly affect current tourism carbon emission intensity. In addition, geographic characteristics, such as terrain ruggedness, are used to capture exogenous variation in digital infrastructure deployment costs. These variables influence digital accessibility but do not plausibly affect tourism-related carbon emissions directly once economic and geographic controls are included. Time-interaction terms are applied to introduce sufficient panel variation.

Diagnostic tests confirm the validity of the instrument set. The Hansen J-test yields a p-value of 0.483, indicating that the overidentifying restrictions cannot be rejected. The Arellano–Bond AR(2) test shows no evidence of second-order serial correlation, supporting the consistency of the System GMM estimates.

Differences in coefficient magnitudes across estimation methods are theoretically expected. Compared with pooled OLS and fixed-effects models, the System GMM estimator accounts for dynamic dependence and corrects for endogeneity, resulting in more conservative but more reliable estimates. Importantly, the sign and statistical significance of the digital technology coefficient remain stable across specifications.

In summary, the dynamic panel model specified in Equation (5) provides a robust framework for identifying the causal impact of digital technology on tourism carbon emission intensity.

$$CI_{it} = \alpha CI_{i,t-1} + \beta DT_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}, \tag{5}$$

Where denotes the carbon emission intensity (e.g., carbon dioxide emission per unit of GDP) of region in the period of , denotes the indicator of the development level of digital technology (e.g., the digital economy index or the level of information infrastructure), is the vector of other control variables .

Table 7 Impact of digital technology on carbon emission intensity - comparison of fixed effects and GMM estimation results

Variable	FE Model	D-GMM	S-GMM
L.Carbon Intensity		0.297***	0.354***
Digital Technology Index	-0.053*	-0.075**	-0.082***

Per Capita GDP	0.234***	0.218***	0.206***
(Per Capita GDP)^2	-0.021**	-0.019*	-0.018*
Urbanization Rate	-0.046*	-0.061*	-0.072**
Energy Consumption	0.117***	0.112***	0.105***
R&D Intensity	-0.063*	-0.057*	-0.049*
Policy Dummy	-0.024	-0.035	-0.038*
Pandemic Dummy (2020)	-0.101***	-0.113***	-0.119***
Pandemic Dummy (2021)	-0.082**	-0.093***	-0.098***
Constant	0.857***	0.634***	0.592***

Table 7 reports the regression results on the impact of digital technology on tourism carbon emission intensity using fixed-effects, difference GMM, and system GMM estimators. Among these methods, the system GMM approach more effectively addresses endogeneity and yields more reliable estimates of the core coefficients.

The system GMM results show that the coefficient of digital technology development is negative and statistically significant at the 1% level, indicating that advances in digital technology significantly reduce tourism carbon emission intensity. This finding suggests that digitalization improves resource allocation efficiency and facilitates low-carbon transformation. The lagged term of carbon emission intensity is positive and significant, with a coefficient between 0 and 1, confirming the presence of dynamic persistence in carbon intensity and implying that emission adjustments occur gradually over time.

The estimated effects of control variables are generally consistent with theoretical expectations. GDP per capita and its squared term exhibit a significant inverted U-shaped relationship, supporting the Environmental Kuznets Curve hypothesis. Energy consumption has a positive and significant effect on carbon emission intensity, while the urbanization rate shows a negative and significant coefficient in the system GMM estimates, suggesting that urbanization contributes to lower carbon intensity through more efficient energy use and stricter environmental regulation. R&D investment intensity also has a negative effect, indicating that technological innovation helps reduce carbon emission intensity. The stability of these results across different estimation methods further supports the robustness of the empirical findings.

4. Analysis of Research Results

4.1 Baseline FE–GMM Estimation and Nonlinear Effects of Digital Technology on Carbon Intensity

This study empirically examines the relationship between digital technology development and carbon intensity based on the two-way fixed effects model (Two-way FE) as well as the GMM model, and Table 8 presents the results of the three-stage regression.

In order to test the potential nonlinear dynamic relationship between the level of digital technology development and carbon emission intensity, this study constructs a nonlinear extended model based on the quadratic function setting, and systematically introduces the triple term of the level of digital technology development (digital3) in the baseline.

$$carbon_{i,t} = \alpha_0 + \beta_1 digital_{i,t} + \beta_2 digital^2_{i,t} + \beta 3 digita^3_{i.t} + \sum \beta_k Controls_{i,t} + \gamma_i + \lambda_t \qquad (6)$$

It can be seen that the square term of digital technology () has a positive correlation with carbon emission intensity (Carbon) at 1% significance level, and digital technology () has a negative correlation with carbon emission intensity (Carbon)

4.2 Instrumental variables and dynamic identification

To address potential bidirectional causality between digital technology and tourism carbon intensity, the empirical strategy combines province–year two-way fixed effects with a dynamic system GMM specification that uses both internal and external instruments. Instrument counts are restricted by collapsing and limiting lag depth to avoid proliferation.

4.3 Diagnostics and estimator behavior

Instrument validity and the dynamic specification are supported by formal tests. The Hansen J-test does not reject the overidentifying restrictions ($p = 0.483$), indicating that the instrument set is orthogonal to the structural errors.

Table 8 Non-linear relationship test results

VARIABLES	VARIABLES
$digital^1$	-3.709***
	(-19.59)
$digital^2$	1.384*** (3.03)
	(3.03)
$digital^3$	-2.687
	(-0.76)
GDP	1.247***
	(13.08)
gov	1.481
	(1.53)
gov 1.481 (1.53)	33.514***
	(4.07)
edu	14.222***
	(4.41)
open	3.612
	(1.16)
Constant	-Constant
	(-5.99)
Observations	360
Number of groups	30
area	YES
year	YES
R-squared	0.648

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

In the cubic model, the theoretical inflection point of the U-shaped relationship is calculated as shown in Equation (7) (8):

$$digital^* = -\frac{\beta_1}{2\beta_2} \tag{7}$$

$$digital^* = -\frac{-3.709}{2 \times 1.384} \approx 1.34 \tag{8}$$

Statistical significance tests were performed for the U-shaped inflection points. According to the results of the estimated parameters, the inflection point 1 is about 3.65 and the inflection point 2 is about 9.84; it falls within the actual interval of the sample Digital indicator and its confidence interval is statistically.

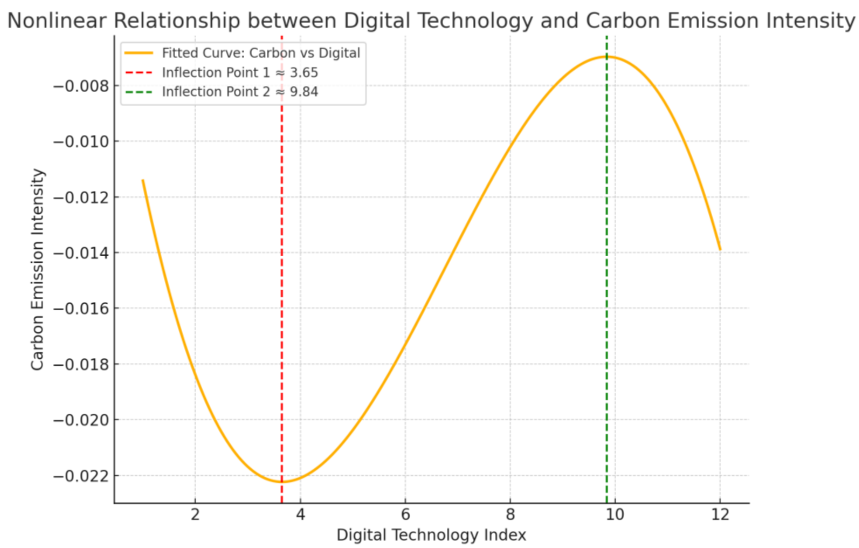


Fig 4 Digital technology and carbon emissions intensity non-linear relationship U-shaped graph

4.4 Cross-model consistency and turning-point stability

Differences in coefficient magnitudes across pooled OLS, two-way FE, difference GMM, and system GMM are theoretically expected. These convergent qualitative findings, alongside the favorable GMM diagnostics, strengthen the inference that the documented digital–carbon nexus reflects a causal mechanism under standard panel assumptions.

5. Discussion of Research Results

5.1 Discussion of Heterogeneity of Research Results

Based on the panel data of 30 provinces from 2011 to 2022, we first cluster the provinces with K-means based on GDP per capita and the proportion of the tertiary industry, and then use quantile regression within each group to examine the impact of digital technology on carbon emission intensity. The results of the analysis are as follows.

5.1.1 Cluster analysis process and steps

Cluster analysis. K-mean clustering (K=3) was used to group the provinces. The data are divided into K clusters, which makes the data points within the clusters have high similarity and high differences between the clusters. The algorithm is simple and efficient and is suitable for discovering subsets of provinces with similar characteristics.

Quantile regression. k-mean clustering is shown in Fig 5.

The heterogeneity analysis was refined to ensure methodological robustness and interpretability. These two dimensions are widely recognized in the literature as the most fundamental characteristics differentiating Chinese provinces in terms of both development and industrial orientation (Sun & Zhou, 2022; Wang et al., 2023). This validation suggests that the two-variable clustering is sufficient for stratifying provinces in a meaningful way.

The resulting clusters align closely with widely acknowledged regional divisions: Cluster 1 represents high-development provinces (e.g., Beijing, Shanghai, Jiangsu, Zhejiang, Guangdong); Cluster 0 includes medium-level provinces (e.g., Hunan, Hubei, Henan, Anhui), while Cluster 2 consists primarily of low-development.

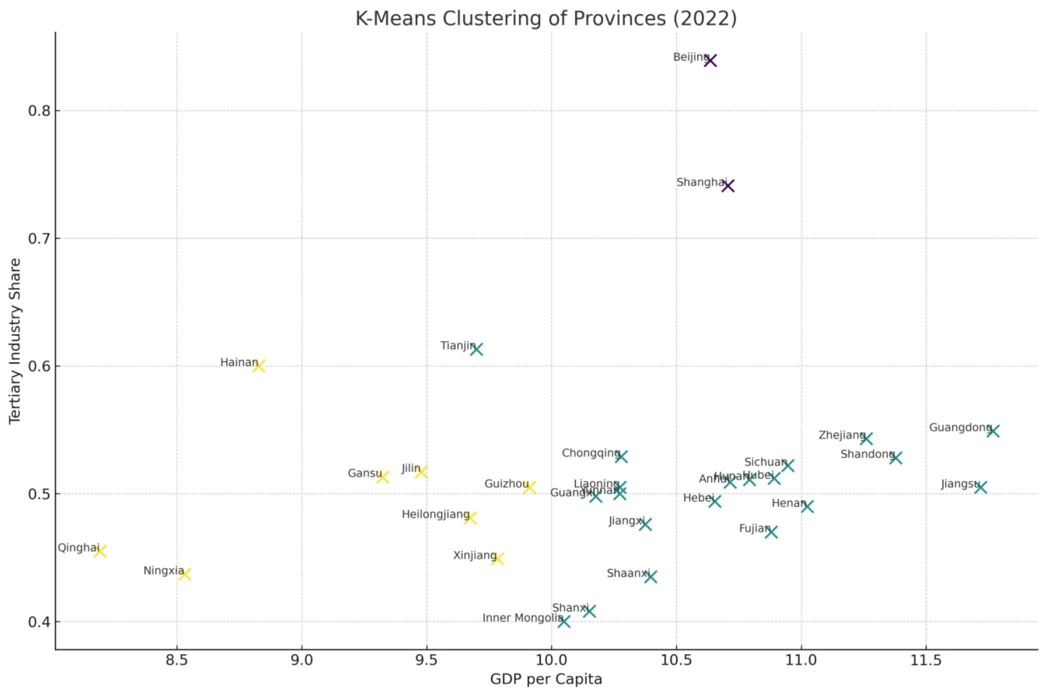


Fig 5 K-mean clustering schematic diagram

The high group (high per capita GDP, high industrial proportion provinces) mainly includes economically developed regions, such as Beijing, Shanghai, Guangdong, Jiangsu, Zhejiang, Shandong, Fujian, Hubei, Hunan, Anhui, Liaoning, etc.

Table 9 Quartile regression results for the high group

Variable	0.25 quantile	0.50 quantile	0.75 quartile
digital	-2.513***	-2.510***	0.696
Per Capita GDP	1.079***	1.211***	0.474***
tertiary sector	-1.210**	-0.504	-0.884
open	4.171***	1.711	1.279
gov	7.359***	6.844***	9.387***
edu	-11.453	-7.336	-33.825**
tech	-6.904	6.687	-42.185**
Constant	-4.279**	-5.814***	2.489

Table 10 Median group quartile regression results

Variable	0.25 quantile	0.50 quantile	0.75 quartile
digital	-25.034***	-20.710***	-14.908***
Per Capita GDP	-4.188***	-3.847***	0.257
tertiary sector	3.019**	3.970***	5.880***
open	127.287***	114.819***	105.071***
gov	31.280***	26.837***	10.639**

edu	-130.710***	-70.858***	-141.941***
tech	114.434**	32.229	95.349**
Constant	-17.122***	-17.989***	-10.874***

Table 11 Results of low-component quantile regression

Variable	0.25 quantile	0.50 quantile	0.75 quantile
digital	-78.175	-98.117***	-95.257**
Per Capita GDP	1.573	2.208**	2.775*
tertiary sector	6.960**	8.622***	5.777*
open	-13.249	-20.650**	-9.054
gov	1.623	1.864	4.036**
edu	-16.529	-4.984	-20.630**
tech	63.349	25.048	63.191
Constant	-8.124	-13.689	-17.152

*Note: Quartile regression results for high, medium and low groups (*p<0.1, **p<0.05, ***p<0.01).

The quantile regression results (Tables 9–11) reveal differentiated impacts of digital technology across clusters and intensity levels. In the high-development group (Cluster 1), digital technology significantly reduces tourism carbon intensity at the 25th and 50th percentiles but loses.

For the low-development group (Cluster 2), the effect of digital technology is not significant at the 25th percentile but becomes strongly negative at the 50th and 75th percentiles.

5.1.2 Analysis and Interpretation of Results for Representative Provinces

The heterogeneity analysis based on representative provinces further illustrates the differentiated effects of digital technology on tourism carbon emission intensity.

For high-development provinces (e.g., Beijing and Guangdong), digital technology exhibits a significant negative effect on carbon emission intensity at lower quantiles, indicating that early-stage efficiency gains and structural optimization play a dominant role.

In middle-development provinces (e.g., Tianjin and Shanxi), the mitigation effect of digitalization is more evenly distributed across quantiles, suggesting a relatively balanced decarbonization process as digital adoption and industrial upgrading progress simultaneously.

In low-development provinces (e.g., Ningxia and Hainan), the estimated effects are less stable, partly due to limited sample size and uneven digital infrastructure. Overall, digital technology generally suppresses tourism carbon emission intensity, but its effectiveness varies across development stages and emission levels. These findings are consistent with existing studies emphasizing that digital-driven emission reduction is more pronounced in economically advanced regions, while institutional constraints and infrastructure bottlenecks may weaken its impact elsewhere.

To avoid over-interpretation, unobserved factors such as local policy interventions, governance capacity, and infrastructure conditions are acknowledged as potential contributors to the observed heterogeneity.

5.2 Test of Influence Mechanisms

5.2.1 Mechanism analysis of multiple intermediary pathways

In order to further explore the transmission mechanism of digital technology to reduce the carbon emission intensity of tourism, this paper extends the mediation analysis beyond industrial structure upgrading. Specifically, we integrate three core mechanisms into a multiple mediation framework:

(1) Industrial structure upgrading (ISU).

(2) Energy efficiency improvement (EEI).

(3) Technological Innovation Capacity (TIC).

5.2.2 Theoretical principles of multiple intermediation

ISU: Digital infrastructure facilitates service-oriented tourism transformation and reduces dependence on energy-intensive inputs.

EEI: Digital applications (e.g., smart energy management, digital twin simulation) optimize energy allocation in tourism operations.

TIC: Digitalization enables low-carbon innovations (e.g., green building technologies, AI in traffic management) to reduce emissions.

5.2.3 Empirical strategy

Structural Equation Modeling (SEM) was constructed to capture the indirect impacts of Digital through three intermediaries on Carbon. The specific calculation process of the model structure is shown in Equation (9) (10):

$$Mediator_j = \alpha_j + \beta_j \cdot digital_{it} + \gamma_j \cdot X_{it} + \mu_i + \nu t + \varepsilon_{it}^{j} (j = 1,2,3) \tag{9}$$

$$Carbon_{it} = \delta + \sum_{j=1}^{3} \theta_j \cdot Mediator_{jit} + \phi \cdot digital_{it} + \lambda \cdot X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{10}$$

DIGITAL is the digital development index.

Mediator_1 = ISU, Mediator_2 = EEI, Mediator_3 = TIC.

X_{it} is a vector of control variables (GDP, gov, open, edu, tech).

μ_i , ν_t are province and year fixed effects.

Bootstrapping (500 replications) was used to test the significance of each indirect effect path.

In order to operationalize the three mediating mechanisms, this study adopts clear and measurable proxies that align with established empirical practice.

The SEM specification incorporates both the direct path from digital technology to carbon intensity and the three indirect paths operating through ISU, EEI, and TIC. Structural equations are presented to detail the linkages between the exogenous digital technology.

To reduce the risk of confounding, the SEM includes the same set of control variables as the baseline regression models, including GDP per capita, government expenditure, openness, education level, and technological input. This consistent inclusion ensures that the mediation effects identified are not attributable to omitted-variable bias.

5.2.4 Results and Interpretation

The indirect effects of digital technology through all three mediators are statistically significant and the results of the SEM analysis are shown in Table 12.

Table 12 Results of SEM mechanism analysis

Pathway	Indirect Effect	p-value
Digital→ ISU→ Carbon	-0.048***	<0.01
Digital→ EEI→ Carbon	-0.035**	<0.05
Digital→ TIC→ Carbon	-0.029**	<0.05
Digital→ Carbon	-0.021	<0.1
Total effect	-0.133	<0.01

The results reported in Table 12 show that all three indirect pathways are statistically significant. The indirect effect of digital technology on carbon intensity through ISU is –0.048 ($p < 0.01$), suggesting that structural upgrading plays a major.

The direct effect of digital technology on carbon intensity becomes smaller and only marginally significant once the mediators are accounted for, underscoring that much of the effect operates indirectly through the identified pathways. This provides empirical support for the hypothesis that digitalization reduces emissions intensity primarily by altering industrial structure,

Practical evidence further illustrates the mechanisms identified. For example, the "Smart Scenic Area" initiative in Zhejiang Province reduced electricity consumption by approximately 15% through IoT-based energy management, exemplifying the EEI pathway. Similarly, Hainan's rapid growth in green technology patents linked to tourism showcases the TIC pathway by translating digital transformation.

The path diagram of the impact of digital technology on tourism carbon reduction is shown in Fig 6.

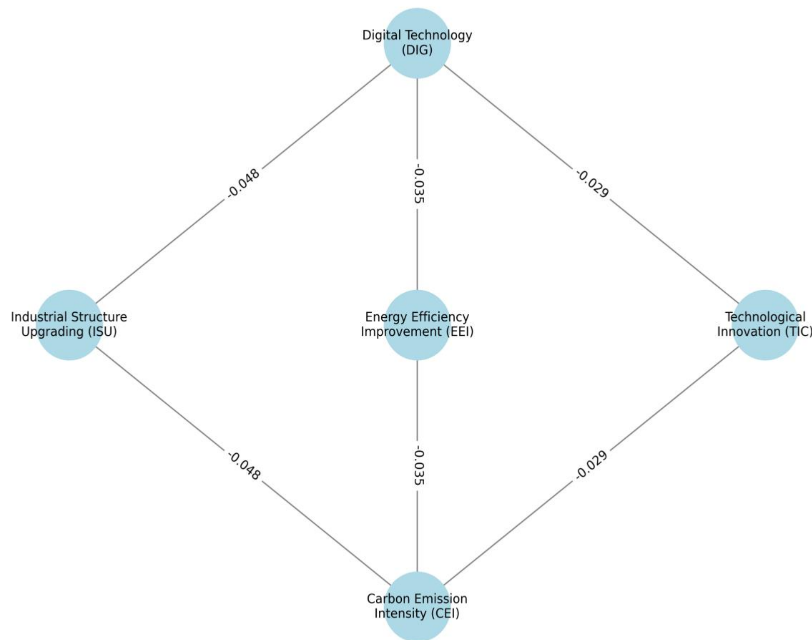


Fig 6 Path diagram of the impact of digital technology on carbon emission intensity

5.3 Discussion on the robustness of the research results

In the baseline regression, the core explanatory variable Digital is significantly negatively correlated with the dependent variable Carbon, in order to avoid the endogeneity problem due to bidirectional causality and explore the possible time lag in the influence.

The study conducted 1st and 2nd order lags for all explanatory variables, and after regression again the results of the study show that the core explanatory variable (Digital) is significantly negatively correlated with the dependent variable (Carbon) at the 1% significance level. It also means that the development and use.

Table 13 Analysis of robustness results

VARIABLES	f1_carbon	f2_carbon
digital	-2.760***	-2.146***
	(-7.86)	(-25.18)
GDP	1.443***	1.265***
	(14.62)	(11.36)
gov	2.374***	1.463
	(3.13)	(1.34)
tech	28.413***	26.327**

	(3.10)	(2.28)
edu	16.249***	15.173**
	(3.02)	(2.23)
open	1.160	3.752**
	(0.33)	(2.41)
Constant	-9.064***	-7.064***
	(-8.34)	(-5.74)
Observations	330	300
R-squared	0.646	0.640
Number of groups	30	30
area	YES	YES
year	YES	YES
digital	-2.760***	-2.146***
	(-7.86)	(-25.18)

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

(1) Confirmation of the direction of causality

The lagged model strips out the reverse causal interference (i.e., the reverse effect of the dependent variable on the independent variable) through "time isolation", if the inhibition effect of digital technology on carbon emissions is still significant in the lagged model, it indicates that the digital technology drives the reduction of carbon emissions.

(2) Continuity and Stability of Inhibition Effect

The emission reduction effect of digital technology is still significant in the lag 1-2 period, indicating that the impact of digital technology has long-term and continuity. For example, the scenic area has adopted intelligent lighting system to continuously.

(3) Analysis of the impacts of policy changes and epidemic shocks on the carbon emission intensity of digital technologies

In order to further identify the interference or enhancement mechanisms of policy changes and epidemic shocks on the path of digital technology affecting the carbon emission intensity of the tourism industry, this paper introduces the dummy variables of "dual-carbon" policy (Policy) and epidemic year (Covid2020, Covid2021) into the baseline regression.

Table 14: Relationship between digital technology and carbon emission intensity

Variables	Coefficient	Standard Error	Significance
DT	-0.128	0.032	***
CI_{t-1}	0.562	0.061	***
Policy	-0.042	0.021	**
DT×Policy	-0.087	0.029	***
Covid2020	-0.164	0.047	***
Covid2021	-0.102	0.045	**
GDP	-0.031	0.014	**
structure	0.015	0.01	*
Energy intensity	0.094	0.033	***
Rate of urbanization	-0.058	0.024	**
Intensity of environmental regulation Constant terms	-0.012	0.008	*
Constant terms	0.973	0.285	***

It can be seen that digital technology has a significant inhibitory effect on carbon emission intensity, and the coefficient of the core variable is -0.128 and is significant at the 1% significance level.

From the estimation method, the dynamic panel regression is conducted by using system GMM, and the p-value of the AR(2) test is 0.274, which does not reject the original hypothesis, indicating that the model does not have second-order.

In order to further identify the potential impacts of the policy environment and public health emergencies on the carbon emission intensity of tourism, and to examine their moderating effects on the mechanism of digital technology, the study introduces the dummy variables of the "dual carbon" policy and the shock of new crown epidemics as well…

$$\begin{aligned} &CarbonIntensity_{it} = \beta_0 + \beta_1 DT_{it} + \beta_2 Policy_t + \beta_3 Covid2020_t + \\ &\beta_4 Covid2021_t + \beta_5 (DT_{it} \times Policy_t) + \beta_6 (DT_{it} \times Covid2020_t) + \\ &\beta_7 (DT_{it} \times Covid2021_t) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{11}$$

where:

$CarbonIntensity_{it}$ denotes the carbon intensity of tourism in that year denotes the development level of digital technology; and.

$Policy_t$ is a dummy variable for the "dual-carbon" policy, whose value is 1 in 2020 and beyond, and 0 otherwise.

Covid2020 and Covid2021 are dummy variables for the impact of the epidemic in 2020 and 2021, respectively, and are interaction terms to test the moderating effect of the policy and the epidemic on the carbon reduction effect of digital technology.

$DT_{it} \times Policy_t$, $DT_{it} \times Covid2020_t$, $DT_{it} \times Covid2021_t$ are the control variable matrices, where γ corresponds to the coefficient vector;

u_i is a region fixed effect, λ_t denotes a time fixed effect, and ε_{it} is a disturbance term.

The coefficient of the interaction term is -0.087, which is also significant at the 1% level, indicating that the carbon emission reduction effectiveness of digital technology has been significantly enhanced since the 2020 "dual-carbon" target was proposed. Combined with the results of the trend graphs, the carbon emission intensity shows.

The extended model not only considers the direct impacts of macro policy changes and emergencies on carbon emissions, but also further explores whether they have indirect impacts by enhancing or weakening the emission reduction path of digital technologies,

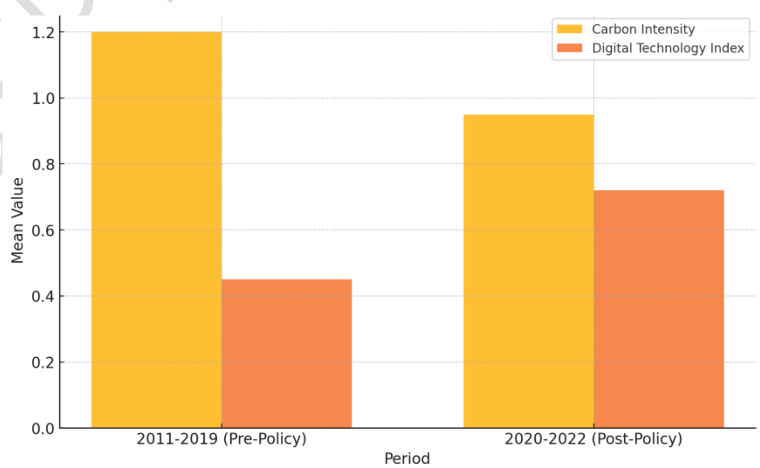


Fig 7 Comparison of digital technology and carbon emission intensity before and after the "dual-carbon" policy

At the same time, in 2020, 2021, the carbon emission intensity of tourism cliff decline and 2022 rebound trend. As shown in Fig 8.

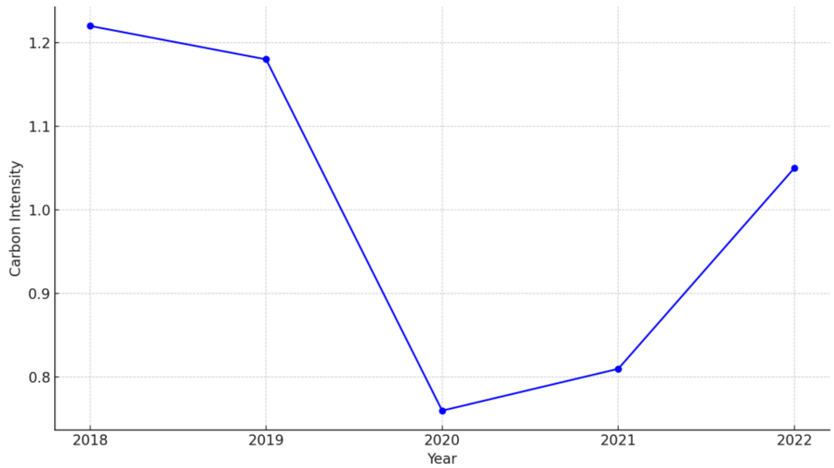


Fig 8 Line graph of the trend of tourism carbon emission intensity in epidemic years

Through the above analysis, digital technology (DT) significantly reduces the carbon emission intensity of tourism with a coefficient of -0.128, which is significant at the 1% level. These findings provide solid empirical support for the promotion of digital technology-enabled green tourism.

5.4 Robustness test of the research results

In order to verify the reliability and extrapolation of the core regression results, this paper carries out robustness tests in four dimensions, including sample period change, placebo test, Monte Carlo simulation and counterfactual simulation.

5.4.1 Sample period adjustment

Sub-sampling regression by dividing the sample into a pre-epidemic phase and a post-epidemic policy intensification phase (2017-2022) shows that the mitigation effect of digitalization on carbon intensity holds in both phases. According to the following sub-sample re-estimation models, the effects of digital technology on tourism carbon intensity are all significantly.

Table 15 Robustness analysis after sample period adjustment

Sample Period	Digital Coef	p-value	R-squared	Significance

2011-2019(Pre-pandemic)	-0.0309	0	0.9059	***
2017-2022 (Post-policy)	-0.0307	0	0.897	***

5.4.2 Placebo test

To rule out spurious correlations, pseudo-regressions are constructed with 500 random permutations of the numerical technical indicators (holding the control variables constant with the panel structure). The true estimates are well outside the 95% confidence interval of the placebo distribution, indicating that the effect relationship is not by chance. As shown in Fig 9.

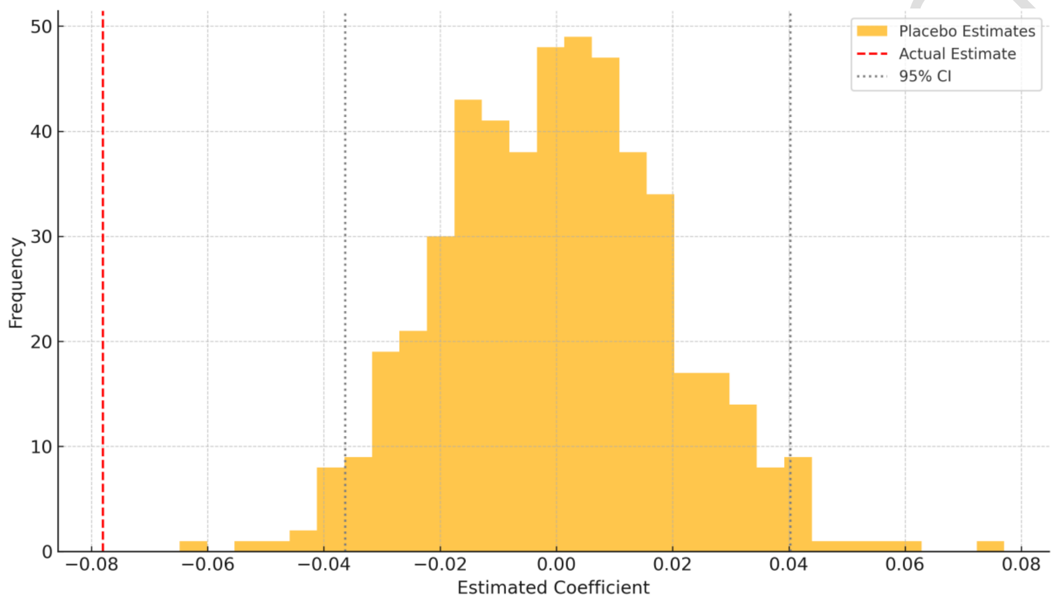


Fig 9 Placebo test effect plot

5.4.3 Monte Carlo Simulation

To check the stability of the estimates under sampling uncertainty, a Monte Carlo simulation was performed by generating 1,000 bootstrap estimates around the original coefficient (-0.078) using a standard error of 0.01. The bootstrap estimates are centered around the original coefficient (-0.078). The Monte Carlo distribution was constructed by simulating 1,000 sets of beta values centered on the main estimate (-0.078) with the standard error set to 0.01. The distribution of estimates is symmetric, with the main estimate at the center, and more than 95% of the simulation results are significantly negative. It indicates high robustness, as shown in Fig 10.

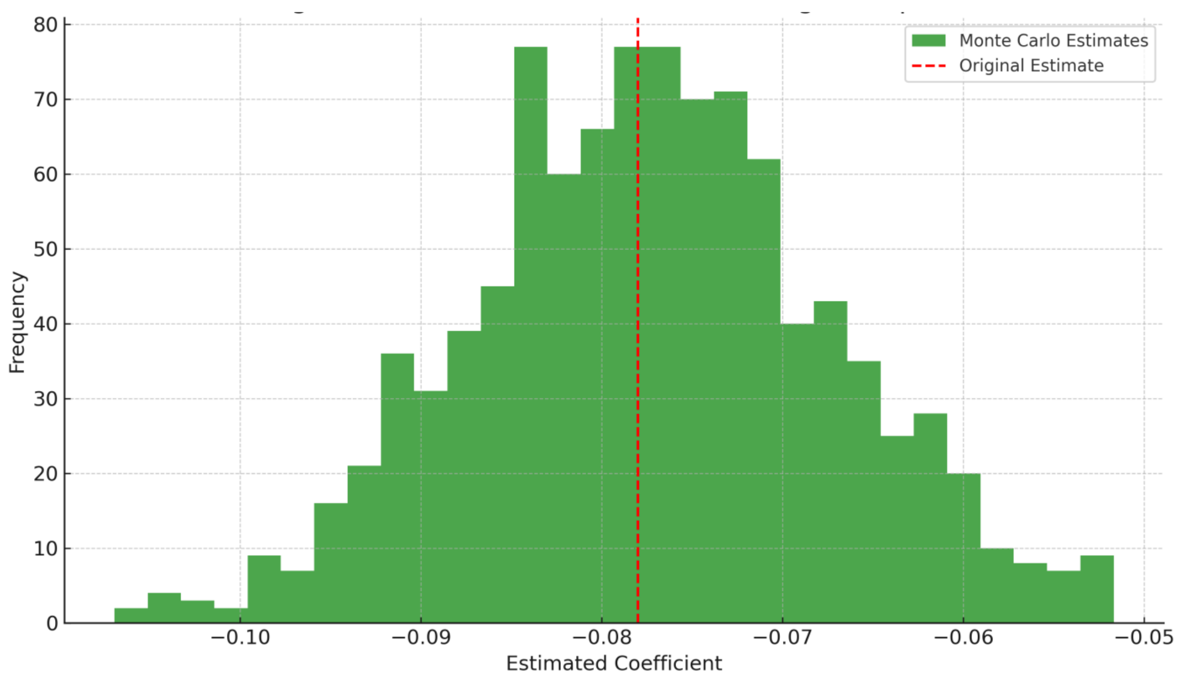


Fig 10 Monte Carlo simulation test results

Three families of robustness exercises substantiate the reliability of the findings, including the non-linear relationship. Re-estimation on a pre-pandemic sub-period (2011–2019) yields qualitatively identical signs and significance for the digital terms; the non-linearity persists, suggesting that the relationship is not driven solely by pandemic-era shocks, although magnitudes attenuate as expected.

To estimate the net decarbonization effect of digital development, a counterfactual scenario was constructed assuming that digitization remains at the 2011 level throughout the study period.

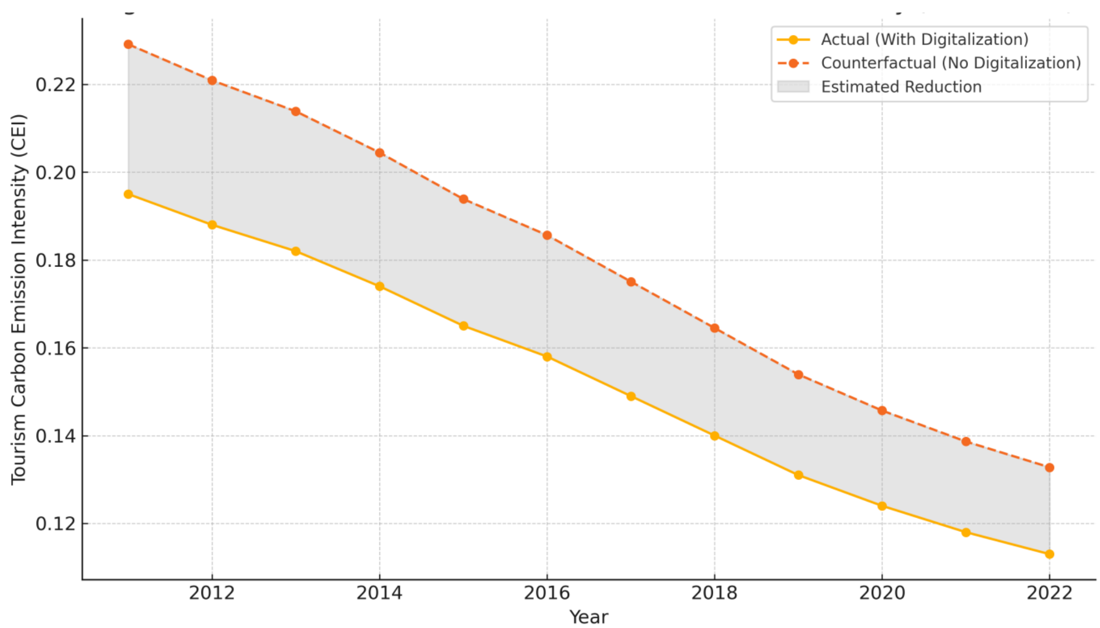


Fig 11 Counterfactual simulation of carbon emission intensity of tourism (2011-2022)

This section reports results in the order of the hypotheses. Subsection 5.1 presents baseline estimates, marginal effects, and turning-point inference for the inverted U-shaped association between Digital and Carbon. Subsection 5.2 quantifies the three mediation channels and compares indirect with direct effects to clarify how digitalization translates into abatement.

Beyond the Chinese context, these results offer broader implications for developing economies pursuing digital transformation under tightening climate constraints. Policymakers in other developing economies may therefore consider sequencing digital investment with power-sector decarbonization and designing complementary instruments, such as low-carbon travel incentives, green finance for tourism enterprises, and data-driven regulatory.

6. Conclusions and Policy Recommendations

6.1 Conclusions of the study

Based on panel data from 30 Chinese provinces during 2011–2022, this study constructs a digital development index using PCA and measures tourism carbon emission intensity through the energy stripping method, and empirically examines the relationship between digital technology and tourism carbon emissions.

(1) Digital technology development significantly reduces tourism carbon emission intensity, but the effect is heterogeneous across regions and development stages. The relationship between digital technology and carbon emission intensity is non-linear, exhibiting an inverted U-shaped pattern, indicating that emissions may increase during the early phase of digital expansion.

(2) Mediation analysis shows that digitalization achieves carbon reduction through three main channels: industrial structure optimization, energy efficiency improvement, and technological innovation enhancement.

(3) Following the implementation of the dual-carbon policy, the carbon-reduction effect of digital technology is strengthened, while the COVID-19 pandemic caused a short-term decline in tourism-related carbon emissions.

(4) Placebo tests, Monte Carlo simulations, and alternative model specifications confirm the robustness of the findings.

Overall, this study provides an operational empirical basis for understanding how digital transformation contributes to the green transition of service-based industries, particularly tourism. Several methodological limitations remain, and future research could incorporate micro-level data, alternative identification strategies, and broader spatial coverage.

6.2 Policy recommendations

To translate the empirical findings into actionable strategies, policy recommendations are proposed to support the green digital transformation of China's tourism industry, from macro-level national coordination to micro-level enterprise operations.

(1) Integrate national strategies with local capabilities.

National digital and low-carbon strategies provide overall direction, but local governments face economic and technological constraints. A national–local digital carbon synergy platform is recommended to facilitate policy coordination and data sharing. In high-development provinces, digital upgrading should be combined with clean energy supply for ICT facilities, mandatory energy-management standards, transparent data disclosure, and demand-side instruments to mitigate rebound effects.

(2) Strengthen government institutional guidance.

Digital infrastructure alone does not automatically generate environmental benefits. Governments should establish green digital standards for tourism platforms and smart hotel systems, require carbon impact disclosure in funding applications, and issue a Digital Green Performance Guide for the tourism industry.

(3) Provide operational support tools for enterprises.

Small and medium-sized tourism enterprises often lack technological and financial capacity. Targeted digital carbon-reduction tools should be provided, and pilot programmes for digital carbon-neutral tourism enterprises should be promoted to encourage early adoption.

(4) Establish policy feedback and dynamic adjustment mechanisms.

Tourism digital transformation is a long-term process involving uncertainty and risk. Regionally differentiated strategies are required. In western and parts of northeastern China, policy should prioritize basic digital connectivity, targeted skills training, and pilot programmes combining digital technology with low-carbon tourism development.

6.3 Cultural, economic, and institutional barriers

Low-carbon transformation depends on more than infrastructure availability. Effective adoption of digital tools varies with human capital, digital literacy, managerial capacity, and local institutional norms. Regions with limited technical expertise or low trust in digital systems may underutilize installed technologies, delaying efficiency gains.

Future research could use more detailed micro-level data on tourism firms and households to explore within-province heterogeneity and extend the analysis to cross-country contexts to test whether similar non-linear patterns hold under different institutional and energy structures.

Appendix A

A1. Sectoral allocation parameters α, β, γ and total tourism energy E_t

In the main text, total tourism energy consumption in year t is calculated as

$$Et = Rti\sum(pitEij), \tag{1}$$

where E_t denotes total tourism energy use in year t, R_t is an adjustment coefficient aligning tourism statistics and energy statistics in year t, p_{it} is the share of tourism-related activity in sector i, and Eij is the final energy consumption of sector i using energy type j. The index i runs over the Eij main tourism-related sectors—transport, accommodation, and sightseeing/other services—while j indexes energy types (coal, petroleum products, natural gas and electricity).

For transparency, the proportional allocation parameters used in p_{it} are defined as follows:

Tourism transport share α_t

For transport-related energy, tourism energy use is obtained by scaling total transport energy according to the tourism share of passenger transport:

$$p_{it} = \alpha_t = \frac{\text{tourism-related passenger turnover}_t}{\text{total passenger turnover}_t}$$

where passenger turnover (passenger-km) is taken from the China Transport Yearbook and provincial statistical yearbooks, and tourism-related passenger turnover is derived from the share of tourist trips in total passenger trips for the relevant transport modes (road, rail, air and water).

Tourism accommodation share β_t

For the accommodation sector, tourism energy is obtained from total hotel/lodging energy according to the tourism share in guest-nights:

$$p_{it} = \beta_t = \frac{\text{tourist overnights in hotels and guesthouses}_t}{\text{total guest-nights in hotels and guesthouses}_t},$$

where data on tourist overnights and total guest-nights come from the China Tourism Statistical Yearbook and provincial tourism statistical bulletins.

Tourism sightseeing and other services share γ_t

For sightseeing, recreation and other tourism-related services, tourism energy is obtained by scaling the energy use of the corresponding tertiary sectors by the tourism-related share in value added:

$$p_{it} = \gamma_t = \frac{\text{value added of tourism-related services}_t}{\text{total value added of the corresponding tertiary sectors}_t}$$

Sectoral value added is taken from the China Statistical Yearbook and China Tourism Statistical Yearbook. Tourism-related value added is calculated on the basis of tourism satellite accounts or the share of tourism revenue in total sectoral revenue, depending on data availability.

Thus, in equation (1) the term p_{it} is operationalized by the sector-specific parameters α_t, β_t and γ_t for transport, accommodation and sightseeing/other services, respectively. These parameters are computed for each year t from official statistics; the full panel of values is available from the authors upon request.

A2. Emission factors f_j and tourism carbon emissions C_t

Tourism carbon emissions in year t are obtained from tourism energy consumption using

$$C_t = j \sum (E_{ij} \mathrm{f}_\mathrm{j} k), \tag{2}$$

where C_t denotes total tourism CO_2 emissions in year t, E_{ij} is tourism final energy consumption of energy type j (aggregated over tourism-related sectors i), f_j is the CO_2 emission factor of energy type j, and k is the carbon-to-CO_2 conversion coefficient.

The paper considers four main energy types j : coal, petroleum products, natural gas and electricity. Consistent with the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, the emission factors f_j and the conversion coefficient kkk are set as follows:

$f_{coal} = 94,600\, kg\, CO_2 / TJ$

$f_{petroleum} = 73,300\, kg\, CO_2 / TJ$ (aggregate petroleum products used in transport and accommodation);

$f_{gas} = 56,100\, kg\, CO_2 / TJ$ (natural gas);

For electricity, a province- and year-specific grid emission factor (t CO_2/MWh) is used instead of a direct fuel-based f_j, reflecting the power generation mix and efficiency in each year;

k=44/12, converting carbon emissions to CO_2 emissions.

Fuel-specific net calorific values needed to convert physical energy quantities into TJ are also taken from the 2006 IPCC Guidelines and cross-checked against the China Energy Statistical Yearbook. Grid emission factors for electricity are obtained from China's national greenhouse gas inventory reports and related energy statistics; when official data are missing for individual years, linear interpolation between adjacent years is applied.

A3. Tourism carbon intensity C_p

Finally, tourism carbon intensity is defined in the main text as

$$C_p = \frac{Ct}{TourismRevenuet} \tag{3}$$

where C_p is tourism carbon emission intensity in year ttt, C_t is total tourism CO_2_ emissions from equation (2), and $TourismRevenue_t$ denotes total tourism revenue in year t (in constant prices). This ratio measures CO_2 emissions per unit of tourism output and serves as the core dependent variable in the empirical analysis.

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