Asian Journal of Applied Economics, 2026, Vol. 33, No. 1, Article No. 330102
ISSN: 2985-1610 (Online)

Provincial Differences in Cultural–Tourism Integration Efficiency and Their Driving Mechanisms in China

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Received: 1 September 2025; Received in revised form: 6 November 2025; Accepted: 14 November 2025

Abstract

Background and Objectives: The integrated development of culture and tourism has become a central pillar of China's strategy for promoting high-quality economic growth, industrial upgrading, and cultural soft power. Beyond its contribution to output expansion, cultural–tourism integration embodies the efficient reallocation of public resources, the coordination of cultural services and tourism markets, and the pursuit of balanced regional development. Despite its strategic importance, substantial disparities persist in the efficiency with which Chinese provinces transform fiscal, institutional, and human resources into cultural and tourism outputs. Existing empirical studies have provided valuable insights into cultural–tourism efficiency, yet many remain limited in scope, focusing on single regions or relying on isolated analytical techniques. Moreover, the structural sources of regional inequality and the mechanisms through which socio-economic and policy factors shape efficiency outcomes have not been systematically examined at the national level. Against this backdrop, this study aims to assess provincial differences in cultural–tourism integration efficiency across mainland China, to identify the structural sources of regional disparities, and to uncover the key driving mechanisms underlying these differences within a unified analytical framework.

Methodology: Using cross-sectional data for 31 provincial-level administrative regions in mainland China for the year 2023, this study adopts a three-step empirical strategy. First, an input-oriented Banker–Charnes–Cooper data envelopment analysis (BCC-DEA) model under variable returns to scale is employed to measure provincial cultural–tourism integration efficiency, focusing on the transformation of fiscal inputs, institutional capacity, and human resources into cultural service provision and tourism outputs. Second, to examine regional disparities and their structural sources, population-weighted Theil indices are calculated for a set of per-capita cultural and tourism indicators, allowing overall inequality to be decomposed into interregional and intraregional components. Third, drawing on the Ritchie–Crouch destination competitiveness framework, a driving-factor indicator system encompassing demand conditions, environmental foundations, policy support, and supporting elements is constructed. An entropy-weighted Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach is then applied to evaluate the relative importance and comprehensive influence of these driving factors across provinces. To enhance robustness and comparability, all indicators are subject to appropriate preprocessing, including winsorization and standardization where necessary.

Key Findings: The results reveal pronounced heterogeneity in cultural–tourism integration efficiency across China's provinces. Overall efficiency levels remain relatively low nationwide, with only about one-third of provinces achieving DEA strong efficiency. Efficient provinces are primarily concentrated in the middle and lower reaches of the Yangtze River and parts of Central China, while many provinces in the Northeast, Northwest, and Southwest exhibit substantial inefficiencies characterized by input redundancy and output shortfalls. The Theil index analysis indicates that disparities in per-capita fiscal input constitute the most significant source of regional inequality, far exceeding disparities observed in public cultural services and tourism consumption outcomes. In contrast, indicators related to public cultural services, such as library circulation and museum visits, display relatively small disparities, suggesting the effectiveness of national equalization policies in this domain. The driving-factor analysis further demonstrates that household consumption capacity, population scale, and fiscal prioritization exert the strongest influence on provincial efficiency differences, whereas macroeconomic development level and higher-education resources play more limited roles in the short term. Provinces with stronger demand-side conditions and clearer fiscal prioritization tend to exhibit higher efficiency, while regions with weak consumption capacity and constrained fiscal support lag behind.

Policy Implications: These findings underscore the need for a coordinated and differentiated policy approach to improving cultural–tourism integration efficiency in China. First, performance-oriented fiscal allocation mechanisms should be strengthened to ensure that public spending is more effectively translated into cultural and tourism outputs, particularly in provinces with persistent inefficiencies. Second, demand-side cultivation policies aimed at enhancing household consumption capacity and expanding diversified cultural–tourism products can generate more immediate efficiency gains. Third, region-specific governance strategies are required to address structural disparities, with western and northeastern provinces benefiting from targeted support that aligns fiscal inputs with local demand conditions and resource endowments. Overall, improving cultural–tourism integration efficiency depends less on expanding resource inputs than on enhancing implementation quality, policy coordination, and demand–supply alignment, thereby promoting more balanced and high-quality cultural–tourism development across regions.

Keywords: Cultural–Tourism Integration; BCC-DEA; Theil Index; Efficiency Measurement; Driving Factors

JEL Classification Codes: C67; R11; Z32

1. Introduction

From the perspective of global socio-economic development, the cultural and tourism industries play an essential role in promoting economic growth, optimizing industrial structures, and improving people's livelihoods (Liu et al., 2025). However, in the context of China's development practices, the deep integration of culture and tourism still faces structural challenges, such as inefficient factor allocation and underdeveloped coordination mechanisms, which to some extent restrict the effectiveness of cultural–tourism integration and hinder its process of high-quality development (Xie et al., 2025).

In response to these challenges, advancing the deep integration of culture and tourism has been elevated to the level of national strategy. General Secretary Xi Jinping has emphasized the principle of "integrating culture into tourism and highlighting culture through tourism," calling for joint efforts of both sectors to enhance national cultural soft power and improve people's spiritual well-being (Guo, 2025). Furthermore, at the end of 2021, the State Council issued the *14th Five-Year Plan for Tourism Development*, which explicitly identified the "integrated development of culture and tourism" as a key task, stressing the need to optimize cultural–tourism mechanisms and build a development model with distinctive Chinese characteristics (State Council of the People's Republic of China, 2021).

Aligned with the strategic requirement of "high-quality development" and the cultivation of "new quality productive forces," the significance of cultural–tourism integration now extends beyond enhancing economic output. At the industrial level, it embodies factor synergy and efficiency spillovers, while at a deeper level, it carries the mission of cultural inheritance and social governance. As highlighted in the 2018 report of the World Tourism Organization, synergy between the cultural and tourism industries constitutes a core driver of integration and innovative development (World Tourism Organization, 2018). This view is echoed by academic research: Panzera et al. (2021) emphasize that synergy between culture and tourism is a critical factor in strengthening their interconnectedness and enhancing destination attractiveness and competitiveness. Chinese scholars likewise argue that coordinated development between the cultural and tourism sectors is essential for shaping a new pattern of cultural–tourism integration (Ren et al., 2025). Against the backdrop of the "triple transformation" of efficiency, momentum, and quality, improving the synergistic efficiency of the cultural and tourism industries has therefore become a core pathway for advancing deep integration and achieving high-quality development.

Although prior studies have generated meaningful evidence on the measurement and evolution of cultural–tourism efficiency, several methodological limitations remain. First, a substantial proportion of empirical research is restricted to a single province, city cluster, or economic region, which limits the ability to capture spatial heterogeneity at the national scale (Lu et al., 2022). Second, many studies adopt a single analytical technique—typically either Data Envelopment Analysis (DEA) for efficiency assessment or the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for comprehensive evaluation—without establishing an integrated framework that systematically links efficiency measurement, regional disparity decomposition, and the identification of driving factors (Wu & Lin, 2022; Zhang & Cheng, 2024). Third, the mechanisms through which socio-economic and policy variables affect efficiency are often addressed at a descriptive or correlational level, rather than being embedded within a coherent theoretical framework such as destination competitiveness, resulting in limited explanatory power regarding the "factor–efficiency" transmission pathway (Liao & Wang, 2024). Finally, although spatial differences are widely acknowledged, most studies do not apply decomposable inequality measures (such as the Theil index) to distinguish the relative contributions of inter-regional and intra-regional disparities, leaving the structural sources of efficiency imbalance insufficiently clarified (Liu et al., 2024).

On this basis, this study constructs a comprehensive research framework using provincial-level data across China from three interrelated dimensions. First, the efficiency of cultural–tourism integration in each province is measured using the Banker–Charnes–Cooper Data Envelopment Analysis (BCC-DEA) model. Second, the Theil index is employed to examine regional disparities in inputs and outputs and to decompose efficiency inequality into inter-regional and intra-regional components. Third, drawing on Ritchie and Crouch's (2003) destination competitiveness framework, a system of driving factors is developed—covering demand conditions, environmental foundations, policy support, and supporting industries—which is further evaluated using the entropy-weighted TOPSIS method to rank and assess their relative importance (Ritchie & Crouch, 2003). Through this systematic approach, the study aims to reveal the spatial patterns, structural disparities, and key drivers of cultural–tourism integration efficiency in China, thereby aligning with the national strategy of "integrating culture into tourism and highlighting culture through tourism," while providing empirical evidence to support balanced and high-quality cultural–tourism development.

Accordingly, this study adopts a three-step analytical framework to ensure internal coherence between efficiency measurement, inequality decomposition, and driving-mechanism identification.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the methodology and describes the data. Section 4 reports the empirical results. Section 5 concludes the paper, and Section 6 discusses policy implications.

2. Literature Review

International organizations and frontier empirical studies generally regard synergies as the key mechanism driving the deep integration of culture and tourism.

The UNWTO’s special report systematically elaborates on the symbiotic relationship between tourism and culture, framing “synergies” as the central theme for organizing policy frameworks and measurement approaches. It emphasizes that integration generates interactive benefits across supply, demand, and governance dimensions—such as co-creation of products, enhancement of visitor experiences, and strengthening of destination competitiveness (World Tourism Organization, 2018). Correspondingly, frontier research based on Chinese provincial and urban agglomeration data has found that cultural–tourism integration significantly increases value-added along the tourism value chain. However, this effect demonstrates threshold and spatial heterogeneity characteristics: when integration levels and agglomeration degrees are higher, synergistic effects become more prominent. This finding suggests that policies must account for regional disparities and factor thresholds (Zeng et al., 2023).

On the basis that “synergy effects” have become a scholarly consensus, existing research frameworks on cultural–tourism integration can be broadly categorized into three types: (1) the industrial integration or value chain perspective, which emphasizes the linkage between cultural content and tourism products and the co-creation of value (Wang et al., 2025); (2) the destination competitiveness framework, which integrates resource endowments, supporting factors, demand conditions, and policy/management into a unified system (Ritchie & Crouch, 2003); and (3) the sustainability or eco-efficiency framework, which focuses on the coordinated development of economic, social, and environmental dimensions (Stoddard et al., 2012). By comparison, the destination competitiveness model not only accommodates the core variables of culture and tourism but also aligns well with the indicator system available at the provincial level. Therefore, this study adopts it as the theoretical framework for constructing the driving mechanisms.

Since its initial formulation, the Ritchie–Crouch destination competitiveness framework has been further extended in terms of sustainability dimensions, governance effectiveness, and multi-level factor linkages (Crouch, 2011). Compared with alternative analytical models such as the Dwyer–Kim competitiveness framework or the coupling–coordination model commonly used in cultural–tourism studies, the Ritchie–Crouch framework provides a more comprehensive configuration of demand, policy, environmental support, and supply elements, making it suitable for multi-dimensional evaluation in regional cultural–tourism research (Azzopardi & Nash, 2017).Moreover, recent comparative assessments indicate that this framework remains one of the most widely applied bases for destination performance and competitiveness analysis in both tourism economics and cultural policy studies, particularly when examining structural factor interactions at the regional scale (González-Rodríguez et al., 2023).

Methodologically, this paper follows a three-step logic of “efficiency measurement—regional disparity analysis—driving-factor identification.” First, in terms of efficiency measurement, the DEA model (particularly the BCC-DEA variant) has been widely applied in the public sector, cultural industries, and tourism industries under multiple-input and multiple-output settings. Its advantage lies in not requiring a pre-specified production function and in handling data with heterogeneous dimensions, making it suitable for characterizing provincial cultural–tourism efficiency levels (Barros et al., 2011; Cooper et al., 2011). Second, for regional disparity analysis, the Theil index, as an entropy-based indicator, not only measures overall disparities but also decomposes them into inter-regional and intra-regional components. It has been widely used in studies on income distribution and industrial balance and has recently been applied to the analysis of tourism resource allocation and cultural service equality, demonstrating its scientific validity in assessing cultural–tourism disparities (Wu et al., 2025). Finally, regarding the identification of driving factors, this paper draws on Ritchie and Crouch's (2003) destination competitiveness framework, selecting indicators across demand, environment, policy, and supporting elements. The entropy method is employed to determine indicator weights, and the TOPSIS method is applied for comprehensive evaluation, thereby identifying the relative contributions and significance of different factors in shaping efficiency disparities.

Through this systematic approach, the study aims to address three core questions: What is the overall pattern of cultural–tourism integration efficiency across Chinese provinces? In which dimensions do regional disparities manifest? And which factors play key roles in driving efficiency differences? These three strands of literature jointly justify the integrated methodological design adopted in this study.

3. Research Design

3.1 Data Sources and Research Scope

The data used in this study are drawn from the *China Cultural Relics and Tourism Statistical Yearbook 2024*, with cross-sectional observations for the year-end of 2023 selected as the research sample. Compiled by the Ministry of Culture and Tourism of the People's Republic of China, this yearbook is authoritative and reliable, providing systematic, comprehensive, and continuous data support for measuring cultural–tourism input–output efficiency.

Regarding the research scope, this study selects 31 provincial-level administrative regions in mainland China as the units of analysis, excluding Hong Kong, Macao, and Taiwan. This definition ensures data availability and horizontal comparability across regions, while facilitating a comprehensive assessment of provincial-level cultural–tourism integration efficiency and its associated regional disparities.

3.2 Indicator System Construction and Data Preprocessing

3.2.1. Input–Output Efficiency Measurement Model

To ensure reproducibility and methodological transparency, this study employs an input-oriented Banker–Charnes–Cooper (BCC) model under the assumption of variable returns to scale (VRS), allowing for both input and output slack variables. Efficiency is quantified as follows: pure technical efficiency (PTE, also denoted as TE) corresponds to the radial contraction coefficient θ_{VRS} under the VRS assumption;

overall technical efficiency (OE) corresponds to θ_{CRS} under the constant returns to scale (CRS) assumption; and scale efficiency (SE) is defined as $SE = OE/TE$. All calculations are conducted using DEAP version 2.1, with linear programming solved through its built-in optimization routines.

In DEA-based efficiency analysis, the rigorous selection of input and output indicators is crucial for ensuring the rationality and robustness of the estimated results. Following the input–output logic of the cultural and tourism industries, this study constructs an indicator system comprising three input indicators and six output indicators, aiming to comprehensively capture the relationship between resource allocation and output performance in cultural–tourism integration.

When applying the BCC-DEA model, the ratio of sample size to the number of indicators must satisfy certain theoretical constraints. According to Cooper et al. (2011), the number of decision-making units (DMUs) should be no less than three times the total number of input and output indicators, that is, $n \geq 3\ (m+s)$. In this study, the sample consists of 31 provincial-level regions as DMUs, with three input indicators and six output indicators, satisfying the condition $31 \geq 3\times(3+6) = 27$. Therefore, the constructed indicator system meets the minimum sample-size requirement and ensures sufficient discriminatory power in the DEA estimation.

Specifically, on the input side, the indicators include: (X1) cultural and tourism expenditure, (X2) number of cultural and tourism institutions, and (X3) number of employees in the cultural and tourism sectors. Together, these indicators correspond to the "supporting factors and management policies" dimension of the destination competitiveness framework, reflecting fiscal investment, organizational capacity, and human capital inputs.

On the output side, the indicators comprise: (Y1) total circulation of public libraries, (Y2) number of services provided by cultural centers and stations, (Y3) number of performances by art troupes, (Y4) number of museum visitors, (Y5) operating revenue of A-level tourist attractions, and (Y6) number of visitors received by A-level tourist attractions. These indicators capture cultural service provision, utilization of cultural and museum resources, vitality of the performing arts, as well as tourism-related economic benefits and market demand, corresponding to the "core resources and market demand" dimension of the framework.

Given that the measurement units of input and output indicators differ, and that the 31 provincial-level regions—including both municipalities and provinces—vary substantially in economic scale and population size, directly using raw data may distort efficiency estimates due to extreme values and scale effects. To satisfy the non-negativity requirement of DEA and enhance cross-indicator comparability, this study adopts a two-step data preprocessing procedure. First, Winsorization (WinsorTwo at the 5% level) is applied to all indicators, trimming the upper and lower 5% of extreme values to reduce the influence of outliers. Second, interquartile range (IQR) scaling is used to rescale all variables, thereby mitigating unit and magnitude differences across indicators.

Winsorization is employed because, unlike direct truncation or z-score transformation, it preserves the original distributional structure while suppressing the leverage of extreme observations—an important consideration for provincial-level socio-economic indicators that often exhibit policy-induced spikes. Similarly, following Boudt et al. (2020), IQR scaling is adopted in preference to min–max or z-score standardization, as it is more robust to skewed distributions and reduces distortions arising from non-normal data (Cao & Obradovic, 2015).

After these preprocessing steps, a standardized indicator system for measuring cultural–tourism resource efficiency is obtained, as reported in Table 1. This processed dataset serves as the basis for the subsequent BCC-DEA efficiency analysis.

Table 1. Standardized Indicator System for Cultural–Tourism Resources

Region	X1	X2	X3	Y1	Y2	Y3	Y4	Y5	Y6
Beijing	1.887	1.233	1.892	0.407	0.875	0.194	0.676	0.529	1.073
Tianjin	0.487	0.407	0.332	0.469	0.368	0.101	0.342	0.216	0.500
Hebei	1.768	2.105	1.636	1.333	1.793	0.884	0.978	0.288	0.555
Shanxi	1.432	1.447	1.074	0.571	0.524	0.886	0.566	0.611	0.518
Neimenggu	1.770	1.271	0.901	0.433	0.501	0.236	0.424	0.187	0.274
Liaoning	0.811	1.316	1.356	0.768	0.397	0.059	0.669	0.325	1.024
Jilin	0.837	0.827	0.524	0.225	0.231	0.072	0.275	0.153	0.274
Heilongjiang	1.063	1.105	0.772	0.173	0.381	0.088	0.473	0.299	0.287
Shanghai	2.508	0.843	1.140	0.541	1.381	0.192	0.691	0.550	0.835
Jiangsu	3.708	2.241	2.419	4.216	4.134	1.159	3.280	1.254	3.506
Zhejiang	5.611	2.557	2.699	4.490	9.220	2.459	1.510	2.492	3.189
Anhui	1.193	2.593	1.509	1.727	1.066	2.512	0.723	1.512	1.268
Fujian	1.562	1.358	1.363	0.974	0.392	0.695	0.696	0.528	1.091
Jiangxi	1.223	1.535	1.188	1.208	0.707	0.353	1.292	4.788	1.890
Shandong	2.365	3.115	3.316	2.004	2.986	1.944	2.227	1.516	2.427
Henan	1.402	2.657	2.097	1.312	1.750	3.741	1.817	0.619	1.140
Hubei	1.983	1.611	1.654	1.141	1.208	2.424	1.284	0.946	1.171
Hunan	2.177	1.896	2.968	1.385	1.514	0.672	2.265	2.365	1.817
Guangdong	4.498	2.363	3.183	4.097	2.138	0.537	1.815	1.288	2.085
Guangxi	1.217	1.259	1.184	0.654	0.459	0.082	0.662	0.746	1.500
Hainan	0.483	0.468	0.635	0.164	0.132	0.223	0.125	0.259	0.274
Chongqing	1.005	1.276	0.978	0.701	0.439	1.101	0.928	1.051	1.171
Sichuan	2.372	2.593	4.341	0.926	0.948	0.519	1.949	4.386	2.506
Guizhou	1.950	1.238	0.969	0.373	0.386	0.148	0.567	0.965	0.963
Yunnan	1.482	1.634	1.248	0.386	0.548	1.260	0.529	1.314	1.024
Xizang	0.983	0.542	0.217	0.011	0.266	0.066	0.000	0.022	0.037
Shaanxi	1.308	1.528	1.737	0.573	0.598	0.562	1.424	0.991	1.128

Region	X1	X2	X3	Y1	Y2	Y3	Y4	Y5	Y6
Gansu	0.840	1.397	0.892	0.312	0.314	0.362	0.911	0.441	0.549
Qinghai	0.461	0.591	0.254	0.048	0.121	0.063	0.035	0.181	0.213
Ningxia	0.532	0.261	0.256	0.150	0.173	0.030	0.186	0.084	0.159
Xinjiang	1.456	1.401	0.968	0.209	1.148	0.217	0.284	0.753	0.634

Source: Author's calculation.

Note: This table presents standardized indicator values for cultural and tourism resources by region. X1–X3 represent input indicators related to fiscal, institutional, and human resource inputs, while Y1–Y6 denote output indicators related to cultural service provision and tourism activity. All values are standardized and therefore unit-free.

3.2.2. Regional Disparity Measurement and the Theil Index

To complement the efficiency analysis and further examine spatial imbalances in cultural–tourism development, this study constructs a per-capita indicator system (see Table 2) to capture the balance and heterogeneity of cultural–tourism inputs and outputs across regions. Using per-capita metrics allows regional disparities to be assessed independently of population size and economic scale, thereby facilitating more meaningful cross-provincial comparisons. Specifically, six indicators are selected:

Z1: Per-capita cultural and tourism expenditure (yuan) — capturing the intensity of fiscal support and the level of government investment in cultural–tourism development.

Z2: Per-capita circulation of public libraries (times) — measuring residents' participation in public cultural services.

Z3: Per-capita number of services provided by cultural centers and stations (times) — reflecting the breadth and vibrancy of cultural activity supply.

Z4: Per-capita number of performances by art troupes (times) — indicating the prosperity of artistic creation and cultural consumption.

Z5: Per-capita museum visits (times) — gauging the utilization efficiency of museum resources and public cultural engagement.

Z6: Per-capita visits received by A-level tourist attractions (times) — reflecting the attractiveness of tourism resources and the scale of market demand.

All six indicators reported in Table 2 are calculated on a per-capita provincial basis. Because many values are numerically close, rounding to three decimal places would reduce discernibility across regions. Accordingly, all figures are reported to four decimal places to enhance differentiation and improve interpretability.

Table 2. Indicator System for Measuring Regional Disparities (Per-Capita Metrics)

Region	Z1	Z2	Z3	Z4	Z5	Z6
Beijing	206.3100	0.6740	0.0044	0.0009	1.2253	8.0512
Tianjin	85.2500	1.2425	0.0030	0.0008	0.9920	6.0117
Hebei	57.1400	0.6523	0.0027	0.0013	0.5238	1.2309
Shanxi	98.7400	0.5956	0.0017	0.0027	0.6468	2.4524

Region	Z1	Z2	Z3	Z4	Z5	Z6
Neimenggu	176.5500	0.6532	0.0023	0.0010	0.7009	1.8781
Liaoning	46.3100	0.6641	0.0011	0.0002	0.6336	4.0172
Jilin	85.5200	0.3472	0.0011	0.0003	0.4663	1.9239
Heilongjiang	82.9400	0.2039	0.0014	0.0003	0.6118	1.5349
Shanghai	241.0000	0.7865	0.0062	0.0008	1.1009	5.5086
Jiangsu	103.9200	1.7883	0.0054	0.0014	1.5239	6.7441
Zhejiang	202.3000	2.4500	0.0154	0.0040	0.9022	7.8920
Anhui	46.5900	1.0203	0.0019	0.0044	0.4680	3.3981
Fujian	89.2100	0.8423	0.0010	0.0018	0.6588	4.2792
Jiangxi	64.7400	0.9674	0.0017	0.0008	1.1339	6.8660
Shandong	55.8200	0.7160	0.0033	0.0020	0.8715	3.9316
Henan	34.1300	0.4834	0.0020	0.0041	0.7335	1.9052
Hubei	81.1600	0.7066	0.0023	0.0044	0.8709	3.2888
Hunan	79.1900	0.7628	0.0026	0.0011	1.3657	4.5371
Guangdong	84.5800	1.1662	0.0019	0.0005	0.5658	2.6916
Guangxi	57.8600	0.4703	0.0010	0.0002	0.5218	4.8936
Hainan	110.6100	0.5698	0.0014	0.0023	0.4757	4.3145
Chongqing	75.2300	0.7944	0.0015	0.0037	1.1519	6.0169
Sichuan	67.7400	0.4001	0.0013	0.0007	0.9223	4.9116
Guizhou	120.5300	0.3487	0.0011	0.0004	0.5811	4.0880
Yunnan	75.7900	0.2985	0.0013	0.0029	0.4486	3.5951
Xizang	643.4900	0.1052	0.0081	0.0019	0.0005	1.6438
Shaanxi	79.0600	0.5246	0.0017	0.0015	1.4272	4.6812
Gansu	81.4500	0.4577	0.0014	0.0016	1.4644	3.6511
Qinghai	185.4400	0.2931	0.0023	0.0011	0.2304	5.8923
Ningxia	174.2200	0.7460	0.0026	0.0004	1.0106	3.5665
Xinjiang	133.9500	0.2910	0.0049	0.0009	0.4336	4.0031

Source: Author's calculation.

Note: This table reports per-capita indicator values used to measure regional disparities.
Z1 denotes per-capita cultural and tourism expenditure (yuan/person).
Z2 denotes per-capita circulation of public libraries (times/person).
Z3 denotes per-capita number of services provided by cultural centers/stations (times/person).
Z4 denotes per-capita number of performances by art troupes (times/person).
Z5 denotes per-capita museum visits (times/person).
Z6 denotes per-capita visits received by A-level tourist attractions (times/person).
All per-capita values are calculated by dividing provincial totals by year-end resident population.

The Theil index is an information-entropy–based measure of inequality that is widely applied in regional and development economics to assess spatial disparities. A key advantage of the Theil index is its ability to incorporate population or other weights into the calculation, thereby providing a more comprehensive depiction of interregional inequality (Cowell, 2000). The theoretical range of the index is [0,+∞), where T=0 denotes perfect equality and larger values indicate greater inequality. In applied studies, heuristic thresholds are sometimes used for descriptive purposes—for example, values below 0.2 indicating relatively small disparities, values between 0.2 and 0.5 indicating moderate inequality, and values above 0.5 suggesting pronounced regional disparities.

In this study, population-weighted Theil indices are computed to quantify per-capita disparities in cultural–tourism inputs and outputs across provinces. Provincial population shares are used as weights to ensure that regions with larger populations exert proportionally greater influence on the aggregate measure. The Theil index is calculated as follows:

$$\boldsymbol{T} = \frac{\mathbf{1}}{\boldsymbol{n}} \sum_{\mathrm{i=1}}^{\mathrm{n}} \frac{\boldsymbol{Z_i}}{\overline{\boldsymbol{Z}}} \ln \left(\frac{\boldsymbol{Z_i}}{\overline{\boldsymbol{Z}}}\right) \tag{1}$$

where Z_i denotes the per-capita cultural–tourism indicator value for region i, $\overline{\boldsymbol{Z}}$ is the national (population-weighted) average, and nnn is the total number of regions. A larger value of Equation (1) indicates more pronounced interregional disparities.

It is worth noting that the per-capita indicators in Table 2 are not standardized when computing the Theil index. This is because the Theil index is scale invariant—that is, multiplying all observations by a common constant does not change T—so additional standardization is unnecessary (Xu et al., 2022).

3.2.3. Construction of the Driving-Factor Indicator System and Data Preprocessing

Following the efficiency measurement and regional disparity analysis, this study constructs a driving-factor indicator system based on the destination competitiveness framework proposed by Ritchie and Crouch (2003). The system encompasses four core dimensions—demand conditions, environmental foundations, policy support, and supporting elements—to capture the multidimensional mechanisms underlying provincial differences in cultural–tourism integration efficiency. Specifically, five indicators are selected:

Per-capita disposable income (D1) and year-end population (D2) capture residents' consumption capacity and the size of the regional market, respectively.

Per-capita GDP (D3) gauges the overall level of economic development and the carrying capacity of the macro environment.

Cultural and tourism expenditure as a share of fiscal outlays (D4) serves as a proxy for fiscal prioritization, reflecting local governments' policy inclination and institutional support for the cultural tourism sector.

Number of students enrolled in regular higher education (D5) measures the contribution of human capital and education/research resources to culture and tourism.

To eliminate unit inconsistencies and mitigate skewness across indicators, all variables are uniformly preprocessed using cross-sectional data for the year-end of 2023.

Specifically, indicators D1, D2, D3, and D5 are first transformed using the natural logarithm, after which all indicators—including D4—are standardized using the Z-score method. Formally, the transformations are defined as follows:

$$\boldsymbol{D_j^*} = \frac{\mathbf{ln}\ \boldsymbol{D_j} - \overline{\mathbf{ln}\,\boldsymbol{D_j}}}{\mathbf{sd}(\mathbf{ln}\ \boldsymbol{D_j})}, \boldsymbol{j} \in \{\mathbf{1},\mathbf{2},\mathbf{3},\mathbf{5}\}. \tag{2}$$

$$\boldsymbol{D_4^*} = \frac{\boldsymbol{D_4} - \overline{\boldsymbol{D_4}}}{\mathbf{sd}\ (\boldsymbol{D_4})}. \tag{3}$$

After the transformations in Equations (2) and (3), a standardized driving-factor indicator system is obtained, as reported in Table 3. This preprocessing strategy is designed to enhance numerical stability and cross-provincial comparability, without materially affecting the relative efficiency rankings.

Table 3. Driving-Factor Indicators

Region	D1	D2	D3	D4	D5
Beijing	2.608	2.424	-0.534	0.268	-0.343
Tianjin	1.083	1.094	-1.089	-1.077	-0.422
Hebei	-0.368	-0.882	0.900	-0.527	0.740
Shanxi	-0.570	-0.282	0.008	0.085	0.072
Neimenggu	0.114	0.609	-0.426	0.574	-0.525
Liaoning	0.103	-0.352	0.229	-1.444	0.258
Jilin	-0.692	-0.955	-0.455	-0.466	-0.092
Heilongjiang	-0.703	-1.263	-0.138	-0.527	0.042
Shanghai	2.729	2.285	-0.382	0.574	-0.465
Jiangsu	1.171	1.647	1.068	0.329	0.970
Zhejiang	1.799	1.144	0.771	3.448	0.375
Anhui	-0.176	-0.179	0.678	-1.199	0.582
Fujian	0.687	1.247	0.230	0.696	0.246
Jiangxi	-0.237	-0.386	0.320	-0.832	0.560
Shandong	0.262	0.274	1.270	-0.466	1.125
Henan	-0.677	-0.848	1.233	-1.383	1.229
Hubei	-0.152	0.413	0.622	-0.099	0.740
Hunan	-0.083	-0.211	0.761	0.085	0.704
Guangdong	0.956	0.720	1.537	0.329	1.097
Guangxi	-0.723	-1.137	0.446	-0.282	0.517
Hainan	-0.339	-0.320	-1.405	-0.099	-1.230
Chongqing	0.068	0.373	-0.089	-0.466	0.209
Sichuan	-0.406	-0.362	1.046	-0.466	0.907
Guizhou	-1.002	-1.129	0.137	1.369	0.010
Yunnan	-0.846	-0.671	0.360	0.024	0.243
Xizang	-0.782	-0.607	-2.641	1.919	-3.134

Region	D1	D2	D3	D4	D5
Shaanxi	-0.445	0.109	0.163	-0.527	0.394
Gansu	-1.264	-1.465	-0.393	-0.527	-0.314
Qinghai	-0.827	-0.680	-2.068	-0.160	-2.460
Ningxia	-0.499	-0.320	-1.827	1.247	-1.674
Xinjiang	-0.786	-0.290	-0.331	-0.404	-0.361

Source: Author's calculation.
Note: This table reports standardized values of driving-factor indicators across regions.
D_1 denotes per-capita disposable income, capturing residents' consumption capacity.
D_2 denotes year-end population, reflecting regional market size.
D_3 denotes per-capita GDP, indicating the overall level of economic development.
D_4 denotes cultural and tourism expenditure as a share of total fiscal outlays, serving as a proxy for fiscal prioritization.
and D_5 denotes the number of students enrolled in regular higher education, reflecting human capital and education/research support.
All indicators are standardized and therefore unit-free; positive (negative) values indicate above-average (below-average) levels relative to the national means.

The values reported in Table 3 are standardized, cross-sectional observations for 2023 covering the 31 provincial-level administrative regions in mainland China. To further evaluate the comprehensive effects of the identified driving factors, this study employs an entropy-weighted Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach to assess provincial cultural–tourism driving forces. Specifically, information entropy and information utility are first computed for each indicator (D1–D5) to derive objective weights, ensuring a data-driven allocation of relative importance across dimensions. The information entropy of indicator j is calculated as:

$$e_j = -\frac{1}{\ln(n)}\sum_{i=1}^{n} p_{ij}\ln(p_{ij}) \tag{4}$$

Second, based on the weighted and normalized indicator matrix, the Euclidean distances from the positive ideal solution and the negative ideal solution are computed for each province, yielding the positive ideal distance (D_i^+) and negative ideal distance (D_i^-). The relative closeness to the ideal solution is then calculated as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, (\mathrm{i} = 1, \dots, 31) \tag{5}$$

In Equation (5), C_i denotes the relative closeness of province i, taking values in the interval [0,1]. Larger values indicate that a province is closer to the ideal state under the combined influence of the driving factors and thus exhibits stronger comprehensive driving force. By integrating the weighted contributions of demand conditions, environmental foundations, policy support, and supporting elements, this approach enables systematic cross-provincial comparison of driving performance and provides complementary evidence to the efficiency measurement and regional disparity analyses, thereby revealing the deeper mechanisms underlying cultural–tourism integration efficiency.

To examine the robustness of the ranking results, a simple sensitivity check is conducted by replacing the entropy-based weights with equal weights. The resulting provincial ranking shows no substantial changes, indicating that the TOPSIS results are stable under alternative weighting assumptions.

4. Research Results

4.1 Efficiency Results for Cultural–Tourism Inputs and Outputs

4.1.1. Overall Efficiency Levels

As reported in Table 4, the input–output efficiency of culture and tourism across China's 31 provinces exhibits pronounced heterogeneity. Nine provinces achieve DEA strong efficiency (TE = SE = OE = 1): Jiangsu, Zhejiang, Anhui, Jiangxi, Shandong, Henan, Hubei, Hunan, and Chongqing. Several provinces lie close to the efficient frontier, such as Tianjin (OE = 0.996), Gansu (0.992), and Shaanxi (0.988).

Most regions fall within the 0.60–0.95 range and display varying degrees of inefficiency—for example, Guangdong (0.926), Guangxi (0.918), Sichuan (0.796), Shanghai (0.723), Hebei (0.762), and Fujian (0.686). Provinces with low efficiency (OE < 0.60) mainly include Xizang (Tibet) (0.359), Neimenggu (Inner Mongolia) (0.378), Jilin (0.404), Heilongjiang (0.489), Qinghai (0.556), Ningxia (0.565), Xinjiang (0.555), Hainan (0.564), Shanxi (0.592), and Beijing (0.574), indicating that inputs in these regions have not been effectively transformed into outputs.

Overall, provinces exhibiting strong efficiency are largely concentrated in the middle and lower reaches of the Yangtze River and in Central China, whereas low-efficiency provinces are more prevalent in parts of the Northwest, Southwest, and Northeast, suggesting a certain degree of spatial clustering.

Table 4. Cultural–Tourism Input–Output Efficiency

Region	TE	SE	OE(θ)	S-	S+	SRC	Type	Efficiency
Beijing	0.62	0.926	0.574	0.353	1.662	0.337	IRS	DEA Inefficiency
Tianjin	1	0.996	0.996	0.098	0.595	0.200	IRS	DEA Inefficiency
Hebei	0.79	0.965	0.762	0.047	1.831	0.603	IRS	DEA Inefficiency
Shanxi	0.68	0.87	0.592	0.343	0.064	0.349	IRS	DEA Inefficiency
Neimenggu	0.467	0.809	0.378	0.343	0.287	0.147	IRS	DEA Inefficiency
Liaoning	0.951	0.918	0.874	0.578	2.541	0.583	IRS	DEA Inefficiency
Jilin	0.588	0.688	0.404	0.153	0.315	0.093	IRS	DEA Inefficiency
Heilongjiang	0.569	0.859	0.489	0.148	1.192	0.206	IRS	DEA Inefficiency
Shanghai	0.849	0.852	0.723	0.936	0.761	0.272	IRS	DEA Inefficiency
Jiangsu	1	1	1	0	0	1	CRS	DEA Strong Efficiency
Zhejiang	1	1	1	0	0	1	CRS	DEA Strong Efficiency

Region	TE	SE	OE(θ)	S-	S+	SRC	Type	Efficiency
Anhui	1	1	1	0	0	1	CRS	DEA Strong Efficiency
Fujian	0.712	0.964	0.686	0.096	0.932	0.599	IRS	DEA Inefficiency
Jiangxi	1	1	1	0	0	1	CRS	DEA Strong Efficiency
Shandong	1	1	1	0	0	1	CRS	DEA Strong Efficiency
Henan	1	1	1	0	0	1	CRS	DEA Strong Efficiency
Hubei	1	1	1	0	0	1	CRS	DEA Strong Efficiency
Hunan	1	1	1	0	0	1	CRS	DEA Strong Efficiency
Guangdong	0.928	0.998	0.926	1.051	5.374	0.968	IRS	DEA Inefficiency
Guangxi	0.933	0.985	0.918	0.123	3.872	0.706	IRS	DEA Inefficiency
Hainan	1	0.564	0.564	0.128	0.219	0.178	IRS	DEA Inefficiency
Chongqing	1	1	1	0	0	1	CRS	DEA Strong Efficiency
Sichuan	1	0.796	0.796	1.559	2.275	1.274	DRS	DEA Inefficiency
Guizhou	0.637	0.984	0.627	0.585	1.795	0.501	IRS	DEA Inefficiency
Yunnan	0.834	0.968	0.808	0.17	0.824	0.791	IRS	DEA Inefficiency
Xizang	1	0.359	0.359	0.312	0.262	0.029	IRS	DEA Inefficiency
Shaanxi	1	0.988	0.988	0	1.983	0.694	IRS	DEA Inefficiency
Gansu	1	0.992	0.992	0.248	3.941	0.666	IRS	DEA Inefficiency
Qinghai	1	0.556	0.556	0.247	0.501	0.115	IRS	DEA Inefficiency
Ningxia	1	0.565	0.565	0.093	0.261	0.061	IRS	DEA Inefficiency
Xinjiang	0.672	0.826	0.555	0.224	0.812	0.254	IRS	DEA Inefficiency

Source: Author's calculation.

Note: TE denotes pure technical efficiency under the VRS assumption (θVRS).

OE(θ) denotes overall technical efficiency under the CRS assumption (θCRS).

SE denotes scale efficiency, defined as SE = OE/TE.

S− indicates input slack (input redundancy), and S+ indicates output slack (output shortfall).

SRC denotes the scale-returns coefficient used to classify returns to scale:

IRS = increasing returns to scale, CRS = constant returns to scale, and DRS = decreasing returns to scale.

4.1.2. Divergence between Technical Efficiency and Scale Efficiency

As shown in Figure 1, provinces exhibit substantial differences between technical efficiency and scale efficiency. In some provinces, scale efficiency is close to 1 while technical efficiency is relatively low—for example, Neimenggu (Inner Mongolia) (TE = 0.467), Jilin (TE = 0.588), and Heilongjiang (TE = 0.569). This suggests that although these regions possess advantages in the scale of cultural–tourism resources, they still face shortcomings in management quality, service delivery, or resource allocation capabilities.

Conversely, Hainan (TE = 1, SE = 0.564), Xizang (Tibet) (TE = 1, SE = 0.359), and Qinghai (TE = 1, SE = 0.556) display high technical efficiency but low scale efficiency, indicating that these regions utilize inputs well under limited scale, yet their overall industry size remains small, constraining development potential.

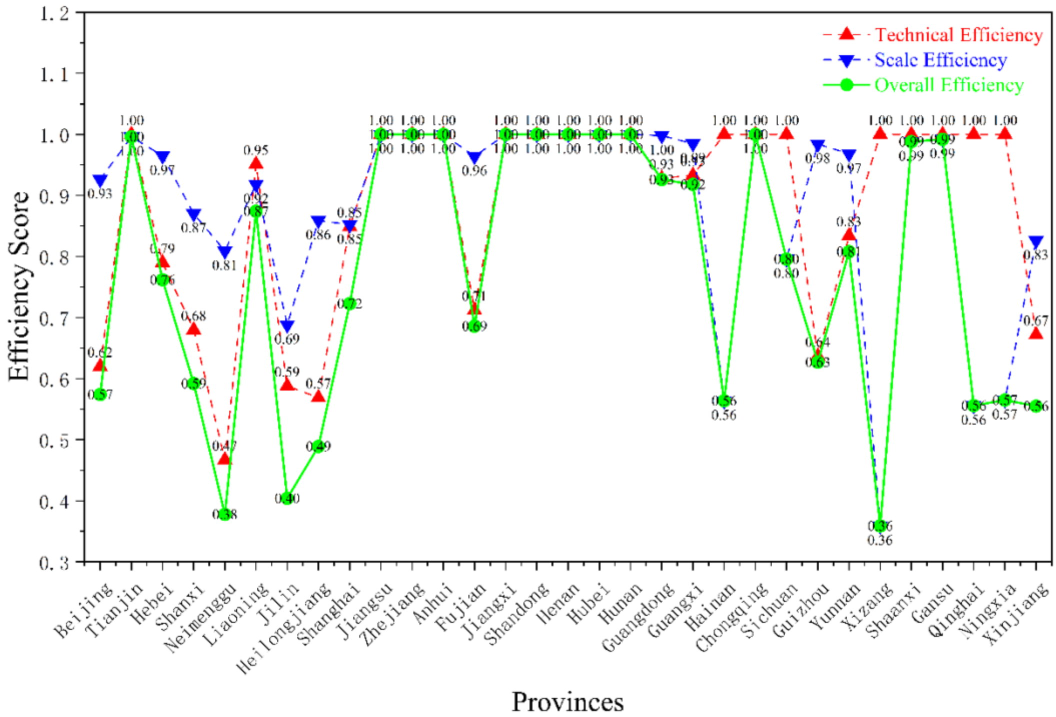

Figure 1. DEA Efficiency Results for Cultural–Tourism by Province

Source: Author's calculation.

Note: Figure 1 compares the technical efficiency (TE), scale efficiency (SE), and overall efficiency (OE) of cultural–tourism development across 31 provinces based on the BCC-DEA model results. The efficiency scores are unit-free (dimensionless) metrics ranging from 0 to 1. A score of 1.00 signifies that the province has reached DEA strong efficiency, operating on the efficient frontier where resource allocation is optimized. Conversely, a score of less than 1.00 indicates relative inefficiency, with values closer to 0 representing higher levels of input redundancy or output shortfall. The plotted values are consistent with the data presented in Table 4 and are rounded to two decimal places for clarity.

4.1.3. DEA Efficiency Status and Directions for Improvement

According to the DEA efficiency evaluation, only about one-third of provinces achieve DEA strong efficiency (TE = SE = OE = 1). The remainder are DEA-inefficient, exhibiting varying degrees of input redundancy and output shortfalls.

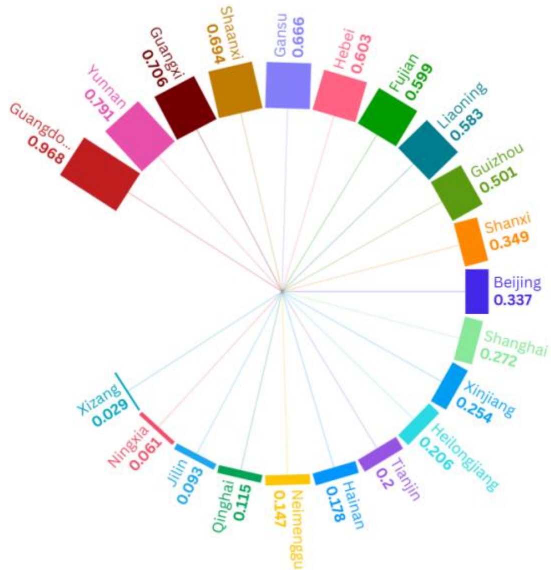

Figure 2. Schematic of the Scale-Returns Coefficient (k) among Non-DEA-Efficient Provinces
Source: Author's calculation.

Drawing on the scale-returns coefficient in Figure 2 (denoted k), most non-efficient provinces fall within the increasing returns to scale (IRS) range—i.e., they operate below the optimal scale. Among them, the most pronounced under-scaling cases with $k<0.2$ include Xizang (Tibet), Jilin, Ningxia, Qinghai, Neimenggu (Inner Mongolia), Hainan; these regions should prioritize expanding effective scale by densifying the supply of high-grade scenic areas and public cultural facilities, improving transport connectivity and source-market organization, and raising the frequency of public cultural services. Provinces with moderate scale shortfalls ($0.2\leq k<0.6$)—Beijing, Shanxi, Heilongjiang, Shanghai, Fujian, Xinjiang, Liaoning, as well as Guizhou—should, alongside measured capacity expansion, reduce input redundancy through project selection and performance management to improve output per unit input. For provinces where the scale issue is relatively mild ($0.60\leq k<0.85$)—such as Shaanxi, Gansu, Guangxi, and Yunnan, as well as Hebei($k=0.603$)—the focus should be on addressing output-side slacks (elevating per-capita service counts, performance events, attraction visitation and revenue) and improving managerial efficiency. Regions near the optimal scale (e.g., Guangdong, $k=0.968$) have limited room for expansion; the key is to optimize output structure and conversion rates (enhancing the conversion of performing-arts and museum activities, extending length of stay and secondary spending). Notably, Sichuan lies in the decreasing returns to scale (DRS) zone, suggesting it has surpassed the optimal scale: further expansion may reduce efficiency, so it should restructure its industry mix, improve resource allocation efficiency, and control the pace of input growth to "improve quality and efficiency."

In addition, based on the slack variables, S- indicates redundancy input, while S+ reflects output deficiency. Provinces with large S- but small S+ (e.g., Shanxi, Shanghai, Neimenggu, Xizang) can be classified as "input-redundant type," whereas those with relatively higher S+ values (e.g., Beijing, Liaoning, Heilongjiang, Guangxi, Guizhou) belong to the "output-insufficient type." This slack-based categorization complements the scale-returns diagnosis and helps clarify the structural sources of inefficiency.

In summary, IRS-type provinces should "expand scale and stimulate demand," near-optimal-scale provinces should "optimize structure and strengthen management," and DRS-type provinces should "constrain scale and raise efficiency." These findings are consistent with the preceding slack analysis and provide a typology-based policy pathway that supports the subsequent regional disparity measurement and driving-factor identification.

4.2 Regional Disparity Results

As shown in Table 5, the Theil indices for the six national cultural–tourism indicators range from 0.2598 to 1.0262, indicating pronounced heterogeneity. Since the Theil index theoretically ranges from 0 (perfect equality) to ln N (complete inequality), values above 0.5 are generally regarded as evidence of substantial structural disparity rather than random fluctuation.

First, on the input side, the Theil index for per-capita cultural and tourism expenditure reaches 1.0262, far exceeding the heuristic threshold of 0.5 for pronounced disparities. This suggests that differences in fiscal support intensity across provinces are highly salient and constitute a major source of regional imbalance in cultural–tourism development.

Second, on the public cultural service supply side, the indices for per-capita public library circulation Z2=0.2598 and per-capita museum visits Z5=0.2821 are relatively low, indicating that national efforts toward equalizing public cultural services have achieved tangible results, yielding a broadly balanced supply pattern. By contrast, the regional disparities for per-capita services provided by cultural centers/stations Z3=0.6524 and per-capita performances by art troupes Z4=0.427 remain notable, reflecting clear regional concentration effects in mass cultural activities and performing-arts resources—patterns closely associated with local fiscal capacity, staffing allocation, and household purchasing power.

Finally, on the tourism consumption side, the index for per-capita visits received by A-level tourist attractions Z6=0.3699 indicates a moderate level of disparity. This suggests that while regional differences in tourism demand exist, the degree of unevenness is clearly lower than that observed for fiscal inputs and mass cultural service provision.

Table 5. Theil Indices for National Cultural and Tourism Indicators

Category	Indicator	Theil Index	Degree of Disparity
Input side	Z1	1.026	Highly unequal
Public cultural services	Z2	0.259	Small disparity
	Z5	0.282	Small disparity
Mass cultural activities	Z3	0.652	Pronounced disparity
	Z4	0.427	Moderate disparity
Tourism consumption	Z6	0.369	Moderate disparity

Source: Author's calculation.

In policy terms, the much larger fiscal gap implies that equalizing the financial capacity to support cultural–tourism development remains a priority, especially for provinces reliant on transfer payments or with limited self-generated revenue. Meanwhile, indicators with lower disparity call for quality-oriented rather than quantity-oriented interventions.

Overall, the regional disparity analysis indicates that fiscal input gaps are much larger than disparities in public cultural services and tourism consumption, and that public cultural services are more balanced than mass cultural activities and tourism-supply outcomes. This pattern points to a structural configuration of "uneven fiscal inputs—pronounced gaps in mass cultural activities—relatively balanced public cultural services," providing empirical ground for subsequent inquiry into the sources of regional disparities and their driving mechanisms.

4.3 Results of the Driving-Factor Analysis

For the weighting of driving factors, the study applies the entropy method to the five standardized indicators, with results reported in Table 6. The information entropy values differ markedly across indicators, implying uneven contributions to differences in cultural–tourism efficiency. Specifically, per-capita disposable income (D1) and year-end population (D2) receive weights of 30.55% and 25.76%, respectively—the two highest—indicating that residents' purchasing power and market size carry the greatest relative importance. The weight for cultural and tourism expenditure as a share of fiscal outlays (D4) is 25.24%, also sizable, suggesting that fiscal prioritization plays a key role at the provincial level. By contrast, per-capita GDP (D3) and number of students enrolled in regular higher education (D5) have comparatively lower weights—10.44% and 8.01%, respectively—indicating that macroeconomic level and education/research support exhibit more limited short-term explanatory contribution.

Table 6. Weights Computed by the Entropy Method

	Entropy value (e)	Information utility (d)	Weight (w)
D1	0.923	0.077	30.550%
D2	0.935	0.065	25.757%
D3	0.974	0.026	10.436%

	Entropy value (e)	Information utility (d)	Weight (w)
D4	0.936	0.064	25.244%
D5	0.980	0.020	8.013%

Source: Author's calculation.

Based on the TOPSIS results with entropy-derived weights (Table 7), the composite performance of cultural–tourism driving factors across China's 31 provinces exhibits marked spatial differentiation. Overall, the Yangtze River Delta and other developed eastern regions hold clear advantages: Zhejiang (C = 0.796, 1st), Shanghai (C = 0.685, 2nd), Beijing (C = 0.661, 3rd), and Jiangsu (C = 0.577, 4th) rank at the top, indicating relatively complete driving systems in terms of income levels, population size, fiscal prioritization, and higher-education and research resources. Coastal provinces such as Fujian (C = 0.534, 5th) and Guangdong (C = 0.518, 6th) also display strong driving capacity.

By contrast, the central–western and northeastern regions show lower composite driving levels. Gansu (C = 0.175, 31st), Qinghai (C = 0.196, 30th), Heilongjiang (C = 0.211, 29th), and Jilin (C = 0.217, 28th) are at the bottom, indicating shortfalls in the economic environment, population scale, and educational resources, which limit their support for cultural–tourism integration efficiency. Provinces such as Henan (C = 0.244, 27th), Guangxi (C = 0.248, 26th), and Xinjiang (C = 0.249, 25th) also lag, highlighting weaknesses in the effectiveness of fiscal spending and human-capital accumulation.

Table 7. TOPSIS Results (Relative Closeness C)

Region	Positive Ideal Distance (Di^+)	Negative Ideal Distance (Di^-)	C	Ranking
Beijing	0.448	1.749	0.796	1
Tianjin	0.766	1.668	0.685	2
Hebei	0.842	1.639	0.661	3
Shanxi	0.943	1.286	0.577	4
Neimenggu	0.994	1.139	0.534	5
Liaoning	1.052	1.132	0.518	6
Jilin	1.33	1.015	0.433	7
Heilongjiang	1.202	0.905	0.430	8
Shanghai	1.361	0.873	0.391	9
Jiangsu	1.362	0.823	0.377	10
Zhejiang	1.490	0.890	0.374	11
Anhui	1.399	0.790	0.361	12
Fujian	1.388	0.777	0.359	13
Jiangxi	1.397	0.77	0.355	14
Shandong	1.563	0.816	0.343	15

Region	Positive Ideal Distance (Di^{+})	Negative Ideal Distance (Di^{-})	C	Ranking
Henan	1.553	0.681	0.305	16
Hubei	1.526	0.668	0.304	17
Hunan	1.502	0.655	0.304	18
Guangdong	1.620	0.658	0.289	19
Guangxi	1.645	0.648	0.283	20
Hainan	1.591	0.619	0.280	21
Chongqing	1.623	0.62	0.276	22
Sichuan	1.611	0.606	0.273	23
Guizhou	1.521	0.567	0.272	24
Yunnan	1.625	0.538	0.249	25
Xizang	1.690	0.557	0.248	26
Shaanxi	1.811	0.586	0.244	27
Gansu	1.697	0.469	0.217	28
Qinghai	1.746	0.468	0.211	29
Ningxia	1.696	0.413	0.196	30
Xinjiang	1.885	0.400	0.175	31

Source: Author's calculation.

From the overall pattern, provinces with higher TOPSIS composite scores are concentrated in the eastern coastal and economically developed regions, whereas most provinces in the central–western and northeastern regions score lower. This aligns with the earlier DEA efficiency measurements and Theil index results: regions with stronger driving factors tend to exhibit higher efficiency, while provinces with weaker drivers show low efficiency and input–output mismatches. These findings further confirm that cultural–tourism integration is constrained by heterogeneous, multi-dimensional drivers, and they provide region-differentiated empirical evidence to inform subsequent policy interventions.

5. Conclusion

Using 2023 cross-sectional data for 31 provincial-level administrative regions, this study develops a three-step research pathway—efficiency measurement—regional disparity identification—driving-factor evaluation—to systematically reveal the spatial configuration and formation mechanisms of provincial cultural–tourism efficiency in China. The DEA results indicate that the national level of cultural–tourism efficiency is generally low: only about one-third of provinces reach DEA strong efficiency, mainly in the Yangtze River Delta and parts of Central China, where fiscal inputs, public cultural services, and tourism outputs are better matched. By contrast, the Beijing–Tianjin–Hebei region, the Northeast, and parts of the West commonly exhibit input redundancy and output insufficiency, which highlights the interrelated nature of inefficient resource utilization and regional imbalance. This pattern reflects the core challenge of balancing input allocation with output performance across China's diverse provinces.

Further analysis using the Theil index uncovers a clearly structured source of regional disparities. Per-capita fiscal input shows the most pronounced difference (T = 1.0262) and is the core driver of overall inequality, whereas disparities in public cultural services and museum visits are relatively small, suggesting that national policies equalize cultural services. Nevertheless, uneven allocation of fiscal resources remains the principal bottleneck constraining overall efficiency improvement. These results imply that interregional disparities manifest not only in the scale of inputs but also in structural misallocation.

Regarding driving factors, the entropy-weighted TOPSIS evaluation shows that household consumption capacity (D1), population size (D2), and fiscal prioritization (D4) have the greatest explanatory power for cultural–tourism efficiency, while the roles of per-capita GDP (D3) and higher-education resources (D5) are relatively limited. Top-performing regions such as Zhejiang, Shanghai, and Jiangsu exhibit advantages in demand–policy coordination, whereas lower-ranked provinces—Gansu, Qinghai, and Heilongjiang—reflect a dual shortfall in fiscal support and consumer purchasing power. Accordingly, improving cultural–tourism efficiency hinges on optimizing the allocation efficiency of fiscal resources, strengthening household consumption capacity, and leveraging population-scale advantages to drive coordinated development—thereby fostering a more balanced and efficient pattern of cultural–tourism integration across regions.

Methodologically, this study demonstrates the value of integrating DEA, Theil decomposition, and entropy-weighted TOPSIS within a unified analytical framework for jointly analyzing efficiency, regional disparities, and driving mechanisms. More broadly, the integrated efficiency–disparity–driver framework developed in this study provides a transferable analytical reference for emerging Asian economies seeking to promote balanced and high-quality development in culture- and tourism-related industries.

6. Policy Implications

6.1 Optimizing the Structure of Fiscal Inputs and Enhancing Spending Performance

The empirical results indicate that disparities in fiscal inputs constitute the primary structural source of provincial imbalances in cultural–tourism integration efficiency. In several provinces, relatively high levels of fiscal input coexist with low efficiency outcomes, reflecting a mismatch between resource allocation and output performance. To address this issue, a shift toward performance-oriented fiscal allocation mechanisms is warranted, accompanied by strengthened monitoring and evaluation of fund utilization to ensure that public spending is effectively translated into cultural and tourism outputs.

In regions with persistently low efficiency—particularly in Western and Northeastern China—fiscal resources should be allocated more strategically toward public cultural services, tourism-related infrastructure, and region-specific characteristic projects. Such targeted allocation can help reduce resource waste, improve input–output alignment, and enhance the overall effectiveness of fiscal support for cultural–tourism integration.

6.2 Expanding Market Demand and Cultivating Diversified Cultural–Tourism Consumption

The results show that per-capita disposable income and population size play a significant role in shaping provincial differences in cultural–tourism efficiency, underscoring the importance of demand-side conditions. Consistent with prior research identifying consumption capacity and market scale as key long-term drivers of tourism development (Song et al., 2012), policies aimed at strengthening household purchasing power are likely to generate more immediate efficiency gains.

Accordingly, policy efforts should prioritize increasing urban and rural household incomes and enhancing the cultural–tourism consumption capacity of middle- and lower-income groups. At the same time, the development of diversified cultural–tourism products—such as digital cultural tourism, immersive experiences, red tourism, and other emerging formats—can enrich the supply structure and stimulate demand. By fostering an urban–rural, multi-tiered, and diversified consumption market, these measures can contribute to improving cultural–tourism efficiency from the demand side.

6.3 Strengthening Education and Research Support and Promoting Interregional Collaborative Governance

Education and research resources provide an important foundation for cultural–tourism development by enhancing human capital quality and supporting long-term industrial upgrading (Liu & Wall, 2006). Although their short-term explanatory power for efficiency differences appears limited, universities and research institutes remain critical for cultivating innovation capacity and improving the sophistication of cultural–tourism products and services. Strengthening interdisciplinary collaboration and industry–academia–research linkages can therefore support sustained improvements in competitiveness.

In addition, interregional collaborative governance and resource sharing should be further encouraged to address pronounced spatial heterogeneity in cultural–tourism development. Enhanced coordination among eastern, central, and western regions can facilitate complementary specialization, reduce duplication of investment, and promote knowledge diffusion. Such cross-regional cooperation can help establish a pattern of co-construction and shared development that advances economic performance, cultural transmission, and social governance in a more integrated and balanced manner.

Overall, these policy implications indicate that improving cultural–tourism integration efficiency relies less on expanding resource inputs than on strengthening implementation quality and policy alignment. Performance-oriented fiscal management, demand-side stimulation tailored to local conditions, and flexible governance that accounts for regional heterogeneity are therefore essential for translating public support and market potential into sustainable efficiency gains.

7. References

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