PANORAMA SCHOLARLY GROUP PSG

Global Review of Humanities, Arts and Society (*GRHAS*)



From Resource Endowment to Innovation-Driven Development: A Quantitative Analysis of the Integration Dynamics in Regional Cultural Tourism

Lili Mou[a], Pengcheng Wang[a,] *

[a]*School of Literature and History, WeiFang University, 261061, WeiFang, China*

ARTICLE INFO

Keywords:
Cultural Tourism Integration
Dynamic Capabilities
Resource-Innovation Gap
Resource Curse
AHP-FCE Model

DOI: *https://doi.org/10.63802/grhas.V2.I1.262*

ABSTRACT

This study addresses the critical transition of regional cultural tourism from traditional resource-dependency to an innovation-driven paradigm. Grounded in Dynamic Capabilities Theory, we develop a quantitative AHP-FCE framework to evaluate this structural shift. Using Shandong Province as an empirical case, the assessment yields a "Good" integration score (0.764), primarily driven by static heritage endowments and economic scale. However, a significant "Resource-Innovation Gap" emerges: technological innovation, despite being the highest-weighted dynamic driver, significantly lags behind traditional resource utilization. This imbalance suggests potential constraints in the efficiency of resource-to-innovation conversion. By providing a transferable diagnostic tool, this study suggests that shifting focus from physical expansion toward digital R&D and talent cultivation can help heritage-rich destinations mitigate the "resource curse" and foster a sustainable cultural tourism ecosystem.

1. Introduction

The global cultural tourism sector is currently experiencing a profound structural transition (Bekele & Raj, 2025; Kumar et al., 2024). For decades, the dominant growth model for heritage-rich destinations—ranging from ancient cities in Southern Europe to historical capitals in East Asia—has been heavily anchored in a "resource-dependent" logic. This traditional approach relies on the sheer volume and physical appeal of cultural endowments, exploiting static assets through mass tourism and traditional ticket-based economies (Richards, 2018; Zhang & Chen, 2024). However, as the digital economy matures and consumer preferences shift toward immersive and experiential consumption (Buhalis et al., 2023; Wu et al., 2024), this endowment-driven model increasingly exhibits signs of a regional "resource curse" (Auty, 1993; Holzner, 2011; Zhong et al., 2024; Zhou et al., 2023). Destinations rich in historical heritage often suffer from institutional lock-in and a chronic lack of endogenous innovation, rendering their massive cultural assets increasingly rigid in a highly competitive global market (Celdrán-Bernabéu et al., 2025). Consequently, the contemporary challenge for destination management is no longer merely the preservation or marketing of cultural resources, but rather the structural transition toward an "innovation-driven" growth trajectory.

To understand this transition, this study introduces the concept of Innovation Conversion Efficiency (ICE) (Ahachmi et al., 2024), grounded in the Dynamic Capabilities Theory (Teece et al., 1997). In the context of cultural tourism, traditional heritage endowments can be viewed as "zero-order" static capabilities. While they provide the foundational raw material for tourism, they cannot automatically generate sustainable competitive advantage in a fast-changing digital landscape. Instead, higher-order "dynamic capabilities"—particularly technological innovation in areas such as digitalization, R&D, and smart infrastructure—are required to continuously sense, seize, and reconfigure these static assets into new value propositions (Eisenhardt & Martin, 2000; Jiang & McCabe, 2021; Anica-Popa et al., 2025; Zhang, 2025). Therefore, in this study, Innovation Conversion Efficiency (ICE) is formally defined as the systemic capability of a destination to reconfigure static heritage endowments (R) into dynamic

* Corresponding author. e-mail: 1010179373@qq.com

© **The Author(s).** This article is published in Global Review of Humanities, Arts and Society under the terms of the **Creative Commons Attribution 4.0 International License (CC BY 4.0)**, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

market advantages (V) through technological and institutional intermediaries (T) (Teece et al., 1997).

Despite the growing consensus on the necessity of this structural transition, empirical evidence reveals a troubling phenomenon: many heritage-heavy regions suffer from a severe "Resource-Innovation Gap." That is, while policymakers aggressively advocate for technological upgrading, the actual transformation process often stalls. Massive investments in tourism infrastructure do not seamlessly translate into high innovation outputs. This structural friction forms the core theoretical puzzle of this paper. To effectively diagnose this gap, a robust quantitative assessment framework is required (Qin et al., 2025). While alternative models like Data Envelopment Analysis (DEA) excel in objective input-output evaluation, they often treat the conversion process as a "black box" and struggle to incorporate subjective policy environments. Similarly, Coupling Coordination Degree (CCD) models effectively measure macro-level synchrony but fail to isolate specific micro-structural bottlenecks. In contrast, the Analytic Hierarchy Process combined with Fuzzy Comprehensive Evaluation (AHP-FCE) framework offers a distinct advantage for diagnosing this structural friction. It explicitly maps the hierarchical tension between subjective institutional goals (what policymakers perceive as important) and objective empirical realities (what the data actually shows), rendering the "gap" mathematically visible.

To empirically investigate this tension, this study selects Shandong Province, China, as a classic global archetype. As the cradle of Confucianism and a globally significant cultural hub, Shandong shares structural similarities with other heritage-heavy destinations. Despite its substantial cultural assets and economic scale, the region faces increasing institutional pressure to move beyond traditional path dependency and accelerate digital transformation. By employing the AHP-FCE model to evaluate the deep integration of cultural tourism in Shandong, this study aims to answer three critical questions: (1) What is the true state of integration when evaluated through a rigorous structural lens? (2) How severe is the structural friction between traditional resource dependency and the desired innovation-driven transition? (3) How can the findings from this specific regional archetype provide a highly transferable diagnostic tool for global destination management?

By addressing these questions, this paper seeks to make a twofold contribution. Theoretically, it conceptualizes the "Resource-Innovation Gap" through the lens of dynamic capabilities, moving beyond traditional input-output analyses. Methodologically and practically, it provides a transparent and highly transferable quantitative framework capable of identifying precise structural bottlenecks in the transition from resource dependency to innovation-driven development, offering actionable insights for policymakers in heritage-rich regions worldwide.

2. Literature Review and Theoretical Framework

2.1. Cultural Tourism Integration: A Structural Perspective

The integration of culture and tourism has long been acknowledged as a crucial strategy for regional sustainable development. Early studies conceptualized this integration primarily as an industrial convergence, where cultural elements are embedded into tourism products to enhance added value. However, as regional economies evolved, scholars increasingly recognized integration not merely as the bundling of products, but as a complex structural transition (Anica-Popa et al., 2025; Zhang & Chen, 2024). This transition entails a shift from exploiting physical heritage endowments toward building resilient, innovation-driven regional ecosystems (Zhang, 2025).

2.2. The "Resource-Innovation Gap" and Dynamic Capabilities

The theoretical foundation of this structural transition can be explained through the lens of Dynamic Capabilities Theory (Nieves & Haller, 2014; Ahachmi et al., 2024). In traditional cultural tourism, regions rely heavily on historical endowments (e.g., ancient architecture, historical sites). These endowments represent "zero-order" static capabilities. While they provide the initial comparative advantage, an over-reliance on them often triggers a regional "resource curse" (Holzner, 2011; Zhong et al., 2024; Zhou et al., 2023). Heritage-heavy destinations frequently suffer from institutional lock-in, where traditional ticket-based economies may limit the motivation for endogenous technological upgrading (Jiang et al., 2024).

To mitigate this curse, developing "dynamic capabilities"—specifically technological innovation in areas such as digitalization and smart platforms—is often considered essential. These capabilities enable destinations to continuously reconfigure their static resources into sustainable market competitiveness (Jiang & McCabe, 2021; Pikkemaat et al., 2019). Consequently, this study conceptualizes the Innovation Conversion Efficiency (ICE) as the critical metric of this transition. It measures a region's systemic capability to mediate between static cultural resources and dynamic technological applications.

Despite recognizing this necessity, empirical reality often reveals a critical systemic failure: the "Resource-Innovation Gap." This gap represents the structural friction between policy aspirations for technological upgrading and the actual lag in empirical execution(Im & Kim, 2022). While policymakers assign high importance to digital transformation, the institutional path dependency of traditional scenic spots can impede hinders the actualization of these innovation goals. Diagnosing and quantifying this specific gap requires a tailored methodological approach.

2.3. Methodological Evolution: Why AHP-FCE?

In evaluating the integration of cultural tourism, existing literature predominantly relies on macro-economic models. Two of the most commonly employed approaches are the Coupling Coordination Degree (CCD) model and Data Envelopment Analysis (DEA) (Li & Liu, 2022; Lu et al., 2023). The CCD model is highly effective at measuring the macro-level synchrony between the cultural industry and the tourism industry. However, it focuses primarily on the balance of two systems and fails to isolate micro-structural bottlenecks within specific criteria (e.g., the friction between heritage scale and R&D capability). Conversely, the DEA model excels at calculating objective input-output efficiency. Yet, DEA treats the institutional transition process as a "black box"; it struggles to incorporate subjective policy environments and institutional priorities, which are central to understanding the gap between policy goals and actual outcomes.

Given these limitations, the Analytic Hierarchy Process combined with Fuzzy Comprehensive Evaluation (AHP-FCE) framework offers a distinct advantage in diagnosing the "Resource-Innovation Gap" (Qin et al., 2025; Tang et al., 2023; Wang et al., 2016). The primary advantage of the AHP-FCE model lies in its ability to explicitly map the hierarchical tension between subjective institutional goals and objective empirical realities. First, the AHP component quantifies the subjective

policy intentions and expert consensus, revealing what the regional ecosystem perceives as structurally important (e.g., assigning the highest weight to technological innovation). Second, the FCE component processes the objective empirical data, calculating the actual performance scores. By juxtaposing the high subjective weight assigned to innovation against its lagging objective fuzzy score, the AHP-FCE model renders the structural friction — the "Resource-Innovation Gap" — mathematically visible. It is this precise diagnostic capability that alternative macro-models lack, making AHP-FCE a highly appropriate methodological choice for this study.

3. Methodology

3.1. Construction of the Evaluation Index System

To scientifically evaluate the integration dynamics of cultural tourism in Shandong Province, this study constructs a hierarchical evaluation index system based on the principles of systematicness, scientific validity, and data accessibility (Du Cros, 2001; Ko, 2005). To capture the theoretical proposition of the "Resource-Innovation Gap," the system consciously shifts away from a purely resource-dependent assessment. Instead, specific indicators for digital capability, R&D expenditure, and policy environments were integrated alongside traditional heritage metrics (Bekele & Raj, 2025; Wu et al., 2024). Specifically, Cultural and Tourism Resources (B3, B4) represent the static Cultural Resources (*R*), whereas Technological Innovation (B5) and Policy Environment (B2) serve as the dynamic intermediaries (*T*). As shown in Table 1, the system is structured into three levels: the Target Layer (A), the Criterion Layer (Level 1, B1-B5), and the Indicator Layer (Level 2, C1-C22). The Criterion Layer consists of five dimensions: Economic Development, Policy Environment, Cultural Resources, Tourism Resources, and Technological Innovation. The complete index set is summarized in Table 1.

Table 1. Evaluation Index System for Cultural and Tourism Integration

Target Layer (A)	Criterion Layer (B)	Code	Indicator Layer (C)	Direction (+/-)	Unit / Data Type
Integration Evaluation	B1 Economic Development	C1	Regional Per Capita GDP	+	RMB / Person
		C2	Resident Disposable Income	+	RMB / Person
		C3	Investment in Fixed Assets of Culture and Related Industries	+	RMB 100 Million
		C4	Proportion of Culture and Tourism Expenditure in Total Fiscal Expenditure	+	%
	B2 Policy Environment	C5	Cultural and Tourism Integration Development Plan	+	Qualitative (Score 1-100)
		C6	Government Expenditure in Culture and Tourism Fields	+	RMB 100 Million
		C7	Talent Training for Cultural and Tourism Integration	+	Qualitative (Score 1-100)
		C8	Total Length of Operating Routes	+	km
		C9	Number of Public Toilets	+	Count
	B3 Cultural Resources	C10	Number of Legal Entities in Culture and Related Industries	+	Count
		C11	Number of Employees in Culture Industry	+	10,000 Persons
		C12	National and Provincial Cultural Industry Demonstration Parks/Base	+	Count
		C13	National and Provincial Representative Intangible Cultural Heritage Projects	+	Count
		C14	National and Provincial Key Cultural Relics Protection Units	+	Count
	B4 Tourism Resources	C15	Total Number of Tourism-Related Enterprises	+	Count
		C16	Total Number of Star-Rated Hotels	+	Count
		C17	Total Number of A-Level Tourist Scenic Spots	+	Count
		C18	Tourism Employees	+	10,000 Persons
		C19	Number of Tourists Received	+	10,000 Persons
	B5 Technological Innovation	C20	R&D Expenditure in Culture and Related Industries	+	RMB 100 Million
		C21	Number of Websites of Enterprises in Culture and Related Industries	+	Count
		C22	E-commerce Sales of Enterprises in Culture and Related Industries	+	RMB 100 Million

3.2. Evaluation Method: AHP-Fuzzy Comprehensive Evaluation

Evaluating the conversion efficiency between cultural resources and technological innovation involves complex, multi-dimensional variables, many of which are qualitative. Therefore, this study adopts a combined approach of the Analytic Hierarchy Process (AHP) and Fuzzy Comprehensive Evaluation (FCE) (Qin et al., 2025; Wang et al., 2016). This hybrid approach scientifically decomposes integration dynamics while addressing the qualitative ambiguity inherent in expert judgments.

3.2.1. Weight Determination (AHP)

The AHP method is utilized to determine the relative weights of the 5 dimensions and 22 indicators. The process involves constructing judgment matrices where experts compare the relative importance of paired factors using the Saaty 1-9 scale. To prevent logical contradictions in expert scoring, the Consistency Ratio (*CR*) must be strictly calculated using the following formulas:

$$CI = \frac{\lambda max - n}{n - 1}$$

$$CR = \frac{CI}{RI}$$

where λ_{max} is the maximum eigenvalue of the judgment matrix, n is the order of the matrix, and RI is the average random consistency index. Only when the calculated CR is strictly less than 0.10 can the judgment matrix be considered to have satisfactory logical consistency, thereby ensuring the mathematical reliability of the derived weights. The specific empirical verification for this study is detailed in the subsequent Data Analysis section.

3.2.2. Comprehensive Evaluation (FCE)

The FCE method, grounded in the conceptual framework of fuzzy sets (Zadeh, 1965), is applied to calculate the final integration score by mapping the determined weights onto a fuzzy membership matrix.

(1) Data Standardization: To eliminate the dimensional differences among the objective quantitative indicators (e.g., regional GDP, R&D expenditure) sourced from the statistical yearbook, the raw data were initially standardized using the min-max normalization method before being presented to the expert panel for fuzzy grading. The formula is expressed as:

$$x_{ij} = \frac{x_{ij} \quad (x_j)}{max(x_j) - min(x_j)}$$

where X_{ij} represents the standardized value, and x_{ij} is the raw empirical data. This ensures all objective data are scaled within a uniform [0,1] interval, facilitating accurate expert assessment.

(2) Evaluation Set: The assessment levels are defined as

V={V_1,V_2,V_3,V_4,V_5}={Excellent, Good, Moderate, Fair, Poor}, with assigned quantitative values of V=(1,0.8,0.6,0.4,0.2)^T

(3) Fuzzy Matrix: The membership matrix R is constructed based on a rigorous statistical distribution of expert ratings. Specifically, the expert panel graded each qualitative and quantitative indicator into the 5 predefined levels. The membership degree r_{ij} was calculated as the proportion of experts selecting a specific level (e.g., if 4 out of 10 experts rated an indicator as 'Good', the membership degree is 0.4).

(4) Result Calculation: The final evaluation vector B is obtained via the fuzzy operator. Specifically, the weighted average operator $W(\cdot,+)$ is adopted to fully retain the information of all factors:

$$B = W \circ R = (w_1, w_2, \ldots, w_n) \begin{bmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{nm} \end{bmatrix}$$

3.3 Data Sources and Expert Panel

The objective quantitative data for this evaluation were primarily sourced from the Shandong Statistical Yearbook (2023) and official developmental reports from the Shandong Provincial Department of Culture and Tourism. For the subjective and policy-oriented indicators, a Delphi method was employed. To ensure a balanced and authoritative assessment, the expert panel consisted of 10 highly qualified professionals carefully selected based on their domains of expertise. Specifically, the panel included 4 university professors specializing in tourism geography and regional economics, 3 senior policymakers from the Provincial Department of Culture and Tourism, and 3 senior executives from leading cultural tourism enterprises.

4. Data Analysis and Results

4.1. Consistency Test of Judgment Matrices

Based on the formulas and thresholds outlined in the methodology, a consistency check was performed for both the Target Layer matrix and the five Criterion Layer sub-matrices using the expert panel's scoring data (Saaty, 1980).

The empirical calculations yielded the following exact CR values for the sub-matrices: Economic Development (CR =0.052), Policy Environment (CR=0.041), Cultural Resources (CR=0.033), Tourism Resources (CR=0.068), and Technological Innovation (CR=0.054). Since the maximum CR value among all matrices is 0.068 (from the Tourism Resources), which is strictly less than the theoretical threshold of 0.10, all judgment matrices exhibit satisfactory logical consistency. Consequently, the resulting weights (presented in Table 2) are highly valid and robust for the subsequent fuzzy synthesis.

Table 2. Evaluation Index System and Weights (Sources: Compiled by authors based on literature and statistical data)

Target Layer (A)	Criterion Layer (B)	Global Weight (B)	Indicator Layer (C)	Local Weight	Global Weight	Rank
Integration Evaluation	B1 Economic Development	0.35	C1 Regional Per Capita GDP	0.56	0.1960	1
			C2 Resident Disposable Income	0.26	0.0910	3
			C3 Investment in Fixed Assets of Culture and Related Industries	0.12	0.0420	7
			C4 Proportion of Culture and Tourism Expenditure in Total Fiscal Expenditure	0.06	0.0210	13
	B2 Policy Environment	0.15	C5 Cultural and Tourism Integration Development Plan	0.50	0.0750	5
			C6 Government Expenditure in Culture and Tourism Fields	0.26	0.0390	9
			C7 Talent Training for Cultural and Tourism Integration	0.13	0.0195	14
			C8 Total Length of Operating Routes	0.07	0.0105	18
			C9 Number of Public Toilets	0.04	0.0060	22
	B3 Cultural Resources	0.14	C10 Number of Legal Entities in Culture and Related Industries	0.50	0.0700	6
			C11 Number of Employees in Culture Industry	0.26	0.0364	11
			C12 National and Provincial Cultural Industry Demonstration Parks/Base	0.13	0.0182	15
			C13 National and Provincial Representative Intangible Cultural Heritage Projects	0.06	0.0084	19
			C14 National and Provincial Key Cultural Relics Protection Units	0.05	0.0070	20
	B4 Tourism Resources	0.16	C15 Total Number of Tourism-Related Enterprises	0.49	0.0784	4
			C16 Total Number of Star-Rated Hotels	0.26	0.0416	8
			C17 Total Number of A-Level Tourist Scenic Spots	0.14	0.0224	12
			C18 Tourism Employees	0.07	0.0112	17
			C19 Number of Tourists Received	0.04	0.0064	21
	B5 Technological Innovation	0.20	C20 R&D Expenditure in Culture and Related Industries	0.72	0.1440	2
			C21 Number of Websites of Enterprises in Culture and Related Industries	0.19	0.0380	10
			C22 E-commerce Sales of Enterprises in Culture and Related Industries	0.09	0.0180	16

4.2. Construction of the Fuzzy Evaluation Matrix (R)

Following the determination of the index weights (W), the next step in the data analysis involved constructing the fuzzy

membership matrix (R). Based on the 10 experts' evaluations of the 22 indicators against the 5 grading levels (Excellent, Good, Moderate, Fair, Poor), the membership degrees were statistically derived.

For instance, regarding the "Cultural and Tourism Integration Plan" (C5), 5 experts rated it as 'Good' and 3 as 'Moderate', resulting in membership degrees of 0.5 and 0.3 for those respective levels. By applying this statistical proportion method across all indicators, the comprehensive fuzzy evaluation matrix $R_{22\times5}$ was established. This matrix served as the foundational quantitative input for the subsequent fuzzy synthesis.

4.3. Comprehensive Evaluation Calculation and Results

With the global weight vector $W_{1\times22}$ (from Table 2) and the fuzzy membership matrix $R_{22\times5}$ fully established, the fuzzy composition operation was executed using the weighted average operator:

$$B = W \circ R.$$

The calculation yielded the final comprehensive evaluation vector for Shandong's cultural and tourism integration:

$$B=(0.282,0.415,0.183,0.080,0.040)$$

According to the principle of maximum membership degree, the highest value in vector B is 0.415, which corresponds to the "Good" level (Level 2).

To further quantify the integration status into a specific metric, the evaluation set values $V=(1,0.8,0.6,0.4,0.2)^T$ were applied to vector B. The final comprehensive score (S) was calculated as:

$$S=0.282\times1+0.415\times0.8+0.183\times0.6+0.080\times0.4+0.040\times0.2=0.764$$

The score of 0.764 suggests that while Shandong Province has established a foundation for cultural and tourism integration, the process remains in a transitional phase.

4.4. Sensitivity and Robustness Analysis

To verify the mathematical robustness of the final comprehensive evaluation score (S=0.764), a rigorous sensitivity analysis was conducted (Tang et al., 2023). The analysis focused on the highest-ranked criterion, Technological Innovation (B5), whose original weight is denoted as W_{B5}. By artificially adjusting this core weight by ±10% to generate a perturbed weight W_{B5}', the weights of all remaining criteria (W_i) were proportionally reallocated to ensure that the sum of the entire weight system strictly remained at 1. The reallocation for the remaining weights was calculated using the following formula:

$$W'_i = W_i \times \frac{1 - W'_{B5}}{1 - W_{B5}}$$

where W_i' represents the newly adjusted weight of any remaining criterion. Under these precise mathematical perturbations, the re-calculated comprehensive scores fluctuated minimally between 0.758 and 0.771. Because the final scores consistently remained within the [0.6,0.8) interval despite the simulated institutional shifts, the evaluation model exhibits strong structural robustness. The results indicate that the integration status remains consistently at the "Good" level, supporting the structural reliability of the evaluation framework.

5. Discussion

5.1. The Trajectory Towards a Paradigm Shift: From Resource Endowment to Innovation-Driven Growth

A key finding of this study points towards a structural trajectory that strongly echoes a paradigm shift in the core drivers of cultural tourism integration. Traditional literature, heavily influenced by the Resource-Based View (RBV), often posits that cultural and tourism endowments are the primary determinants of a destination's competitiveness. However, our AHP results offer a critical re-evaluation of this conventional wisdom. Providing empirical evidence for this transition, Technological Innovation (B5, W=0.20) was found to surpass both traditional Tourism Resources (B4, W=0.16) and Cultural Resources (B3, W=0.14) in systemic importance.

This structural inversion indicates that the integration of culture and tourism has entered a more complex phase. In the digital economy era, the sheer volume of static heritage sites or traditional A-level scenic spots appears no longer sufficient to independently sustain competitive advantage. Instead, the dynamic capability to convert these static assets into immersive, tech-empowered experiences is increasingly recognized as a decisive factor. This transformation is typically driven by R&D, smart tourism, and digital ecosystems (Anica-Popa et al., 2025; Buhalis et al., 2023). This observation aligns with recent theoretical arguments in smart tourism literature. By quantitatively mapping this hierarchical tension, our study suggests that "innovation capital" is increasingly being prioritized over traditional "resource capital" within regional development strategies. This empirical assessment directly responds to the call by recent scholars to move beyond macro-synergy observations and explore the specific structural mechanisms driving digital innovation in heritage-rich destinations(Zhang, 2025) .

5.2. Diagnosing the "Resource-Innovation Gap" in Shandong

Despite its rich cultural heritage resources (e.g., Mount Tai and Confucius' hometown), Shandong's overall integration score is 0.764, placing it at a transitional "Good" level rather than "Excellent." This result provides empirical support for the theoretical proposition of the "Resource-Innovation Gap" introduced in this study.

The gap emerges because strong regional resource endowments do not automatically translate into high innovation conversion efficiency. While Shandong demonstrates considerable structural strengths, such as a high regional GDP per capita and a large number of tourism-related enterprises, the mechanisms that convert cultural value into market value through technological intermediaries remain relatively underdeveloped. In contrast to highly digitized tourism hubs like Zhejiang Province, where cultural IP and digital creative industries are closely integrated, Shandong continues to rely on heavy asset investments and ticket-based revenue models. This persistence may reinforce a degree of path dependence (Zhong et al., 2024; Zhou et al., 2023). The integration score of 0.764 signals a structural imbalance in the region's development. While significantly supported by economic scale (B1), the current model is constrained by the relatively slow technological transformation of its extensive cultural heritage resources.

6. Conclusion and Implications

6.1. Conclusions

This study empirically investigated the structural transition of regional cultural tourism from traditional resource dependency to an innovation-driven ecosystem. Grounded in the Dynamic

Capabilities Theory, we conceptualized the Innovation Conversion Efficiency (ICE) and deployed the AHP-FCE framework to diagnose the precise structural bottlenecks within this transition. Using Shandong Province—one of the world's most heritage-abundant regions—as a classic empirical case, the quantitative assessment yields several critical conclusions.

First, the overall integration of cultural tourism in the region achieves a comprehensive score of 0.764, placing it solidly within the "Good" tier. However, this favorable macro-level performance masks profound micro-structural imbalances. The high score is predominantly sustained by the sheer scale of the region's historical endowments ("zero-order" static capabilities) and raw economic output, rather than advanced technological momentum.

Second, the structural assessment identifies a severe "Resource-Innovation Gap." The AHP results indicate that the regional ecosystem recognizes technological innovation (B5) as the most critical driver for future growth, assigning it the highest weight among all industry-specific and dynamic drivers (surpassing traditional cultural and tourism resources). In contrast to its high subjective prioritization, the objective FCE results reveal a substantial performance lag in technological innovation compared to the region's static cultural and tourism endowments. This misalignment suggests that the region currently faces structural friction: while policy aspirations aggressively target digital transformation, the institutional path dependency of the traditional ticket-based economy severely hinders the actual conversion of static heritage into dynamic market advantages.

6.2. Theoretical Contributions and Global Implications

6.2.1. Theoretical and Methodological Contributions

Theoretically, this study moves beyond the conventional input-output paradigm by integrating Dynamic Capabilities Theory into destination management. It formally conceptualizes the "Resource-Innovation Gap" as the structural friction between zero-order static endowments and higher-order dynamic capabilities. Methodologically, the study demonstrates the distinct diagnostic power of the AHP-FCE framework. It explicitly renders the friction between subjective policy priorities and lagging objective realities mathematically visible, providing a highly transferable diagnostic tool for structural assessment.

6.2.2. Global Applicability and Practical Implications

Although geographically situated in China, Shandong serves as a classic global archetype of a "heritage-heavy, institutionally path-dependent" destination. The diagnostic framework and the resultant "Resource-Innovation Gap" share profound structural similarities with other historical global hubs—such as ancient capitals in Asia (e.g., Kyoto) or cultural epicenters in Southern Europe (e.g., Rome, Athens)—that face similar pressures to modernize their heritage economies (Richards, 2018).Therefore, the findings extend beyond regional boundaries and offer critical insights for global destination governance under similar institutional conditions:

1. Pivoting Strategic Investment from Physical Expansion to Digital R&D

To mitigate the risk of a regional "resource curse," it is suggested that policymakers in heritage-rich destinations globally consider a strategic shift in their focus. Rather than prioritizing the continuous expansion of physical scenic areas or traditional marketing, the findings imply that redirecting capital toward digital infrastructure may be more effective for long-term sustainable development. Furthermore, upgrading from static sightseeing to immersive experiences—utilizing Virtual Reality (VR), Augmented Reality (AR), and AI-driven smart platforms—presents a promising pathway to transform rigid historical assets into high-value dynamic experiences..

2. Addressing Institutional Constraints of the Ticket Economy

The findings suggest that barriers to achieving high innovation conversion efficiency may stem not only from technological limitations but also from institutional constraints. Heritage sites that remain heavily dependent on state-led or traditional ticket-based revenue models may encounter difficulties in generating endogenous incentives for sustained innovation. In this regard, exploring more diversified revenue structures could be beneficial. Cross-sectoral collaboration with digital media, gaming, and creative industries may help foster a more resilient and sustainable cultural ecosystem.

3. Cultivating Cross-disciplinary Talent to Bridge the Gap

The identified lag in innovation performance appears to be significantly linked to existing human capital structures within the sector. Successfully navigating this transition likely requires evolving beyond traditional hospitality-focused training models toward the cultivation of cross-disciplinary professionals who integrate cultural heritage narratives with advanced digital engineering skills. In this context, establishing joint laboratories—comprising tourism administrations, technology enterprises, and academic institutions—could serve as a valuable mechanism to bridge the "Resource-Innovation Gap".

Author Contribution

Lili Mou (First author): Conceptualization, Methodology, Formal analysis, Writing—original draft.

Pengcheng Wang (Corresponding author): Supervision, Project administration, Writing—review & editing.

Compliance with Ethical Standards

Not Required

Funding

This research was supported by the Shandong Federation of Social Science Circles (SFSSC) under the 2024 Humanities and Social Sciences Cooperative Research Project (Grant No. 24H175(C)), titled Research on the Driving Mechanisms, Practical Challenges, and Development Pathways of Digital Transformation in Shandong Cultural and Tourism Enterprises.

Competing Interest declaration

The authors declare that, to their knowledge, they have no financial, personal, or professional relationships that could be construed as a potential competing interest regarding the work described in this manuscript.

Acknowledgments

The authors would like to express their sincere gratitude to the experts from the tourism industry and academia who participated in the consultation and scoring process for the index system. We also thank the anonymous reviewers for their constructive

comments, which have significantly improved the quality of this manuscript.

References

1. Ahachmi, M., Tamanine, R., Lahfidi, A., Brédart, X., & Houssass, M. (2024). Sustainable tourism and destination resilience: A symbiotic relationship based on dynamic capabilities? International Journal of Accounting Finance Auditing Management and Economics, 5(5), 130–149.
2. Anica-Popa, L.-E., Petrică (Papuc), I.-M., Caraiani, C., & Lungu, C.-I. (2025). Smart tourism economics: Introducing a technology-driven competitive advantages framework. Journal of Business Economics and Management, 26(2), 465–487.
3. Auty, R. M. (1993). Sustaining development in mineral economies: The resource curse thesis. Routledge.
4. Bekele, H., & Raj, S. (2025). Digitalization and digital transformation in the tourism industry: A bibliometric review and research agenda. Tourism Review, 80(4), 894–913.
5. Buhalis, D., Leung, D., & Lin, M. S. (2023). Metaverse as a disruptive technology revolutionising tourism management and marketing. Tourism Management, 97, 104724.
6. Buhalis, D., O'Connor, P., & Leung, R. (2023). Smart hospitality: From smart cities and smart tourism towards agile business ecosystems in networked destinations. International Journal of Contemporary Hospitality Management, 35(1), 369–393.
7. Celdrán-Bernabéu, M. A., Mazón, J.-N., Giner-Sánchez, D., Morales-García, J., & Peñarrubia-Zaragoza, M. P. (2025). Smart tourism destinations as open data providers: Barriers and opportunities. Journal of Destination Marketing & Management, 31, 101065.
8. Du Cros, H. (2001). A new model to assist in planning for sustainable cultural heritage tourism. International Journal of Tourism Research, 3(2), 165–170.
9. Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? Strategic Management Journal, 21(10–11), 1105–1121.
10. Holzner, M. (2011). Tourism and economic development: The beach disease? Tourism Management, 32(4), 922–933.
11. Im, J., & Kim, J. (2022). Challenges of smart tourism development from the perspective of destination management organizations. Sustainability, 14(12), 7271.
12. Jiang, Q., & McCabe, S. (2021). Information technology and destination performance: Examining the role of dynamic capabilities. Annals of Tourism Research, 91, 103292.
13. Ko, T. G. (2005). Development of a tourism sustainability assessment procedure: A conceptual approach. Tourism Management, 26(3), 431–445.
14. Kumar, S., Kumar, V., Kumari Bhatt, I., Kumar, S., & Attri, K. (2024). Digital transformation in tourism sector: Trends and future perspectives from a bibliometric-content analysis. Journal of Hospitality and Tourism Insights, 7(3), 1553–1576.
15. Liu, H., & Li, Y. (2022). Coupling coordination between cultural heritage protection and tourism development: The case of China. Sustainability, 14(22), 15421.
16. Lu, M., Duan, Y., & Wu, X. (2023). Evaluation of the coupling and coordination degree of eco-cultural tourism system in the Jiangsu-Zhejiang-Shanghai-Anhui region. Ecological Indicators, 156, 111180.
17. Nieves, J., & Haller, S. (2014). Building dynamic capabilities through knowledge resources. Tourism Management, 40, 224-232.
18. Pikkemaat, B., Peters, M., & Bichler, B. F. (2019). Innovation research in tourism: Research streams and actions for the future. Journal of Hospitality and Tourism Management, 41, 184–196.
19. Qin, X., Peng, Z., Zhang, X., & Yang, X. (2025). Tourism resource evaluation integrating FNN and AHP-FCE: A case study of Guilin. Informatics, 12(2), 54.
20. Richards, G. (2018). Cultural tourism: A review of recent research and trends. Journal of Hospitality and Tourism Management, 36, 12–21.
21. Saaty, T. L. (1980). The analytic hierarchy process. McGraw-Hill.
22. Tang, C., Yang, Y., Liu, Y., & Xiao, X. (2023). Comprehensive evaluation of the cultural inheritance level of tourism-oriented traditional villages: The example of Beijing. Tourism Management Perspectives, 48, 101166.
23. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533.
24. Wang, X., Li, X. R., Zhen, F., & Zhang, J. (2016). How smart is your tourist attraction?: Measuring tourist preferences of smart tourism attractions via a FCEM-AHP and IPA approach. Tourism Management, 54, 309–320.
25. Wu, W., Xu, C., Zhao, M., Li, X., & Law, R. (2024). Digital tourism and smart development: State-of-the-art review. Sustainability, 16(23), 10382.
26. Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8(3), 338–353.
27. Zhang, H., & Chen, J. (2024). The impact of the integration of the culture industry and tourism on regional green development: Empirical evidence from China. Sustainability, 16(8), 3161.
28. Zhang, J. (2025). Patterns of innovation-driven tourism competitiveness: Insights from 270 Chinese cities. Tourism Management, 107, 105063.
29. Zhong, Y., Wu, S., & Li, J. (2024). A revisit of the natural resource curse in the tourism industry: The role of institutional quality. Resources Policy, 88, 104384.
30. Zhou, J., Xia, Z., & Lao, Y. (2023). Does cultural resource endowment backfire? Evidence from China's cultural resource curse. Frontiers in Psychology, 14, 1110379.