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Research on Cultural Tourism Experience Innovation and Industrial Upgrading Based on Digital Technology

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Abstract Against the backdrop of big data technology, the tourism industry is witnessing an abundance of new creative ideas. While digital technology-driven audiovisual spectacles offer tourists new experiences, the industry also faces numerous new challenges. This paper employs factor analysis models and the Tiel index to measure the level of cultural tourism experience innovation and industrial upgrading based on digital technology, respectively. It then combines panel fixed-effects models and data to explore the impact of cultural tourism experience innovation based on digital technology on industrial upgrading. The results show that for every one-unit increase in the cultural tourism experience innovation development index based on digital technology, the regional industrial upgrading index increases by 0.185 units, meaning that the higher the level of cultural tourism experience innovation, the smoother the industrial upgrading process. The empirical findings reveal tourists' willingness to experience digital tourism technology, providing valuable reference for the development of digital tourism in China.

Index Terms factor analysis model, Theil index, panel fixed effects model, cultural tourism experience innovation, industrial upgrading

I. Introduction

In the digital age, information technology is reshaping the development landscape of various industries at an unprecedented speed and scale, including the cultural tourism industry. Traditional cultural tourism models have revealed some limitations under the impact of the digital wave, while the empowerment of digital technology serves as a key to unlocking new opportunities for development [1]. From the subtle shifts in tourist behavior patterns to the profound restructuring of the industry ecosystem, from bold explorations in product innovation to revolutionary changes in marketing and service models, the cultural tourism industry has embarked on a path of innovative transformation and progress [2], [3].

Emerging digital technologies are an important engine for the transformation and upgrading of the cultural tourism industry and its high-quality development [4]. To a certain extent, digital technology is also “experience technology.” The application of digital technologies such as 5G, artificial intelligence, virtual reality, and blockchain has enriched and innovated the forms of expression and experiential content in cultural tourism, marking the accelerated emergence of new business models and formats in the cultural tourism sector [5]-[8]. The comprehensive penetration of digital technology has significantly altered tourist behavior patterns. Travel apps and social media have made it more convenient for tourists to access information, while big data recommendations influence their travel decisions [9]-[11]. Under the support of digital technology, new enterprises and business models are continuously emerging in the cultural tourism industry, and the pace of industrial integration is accelerating [12], [13]. Additionally, digital technology facilitates the exploration and presentation of cultural resources, leading to the emergence of numerous new cultural tourism products [14]. In terms of marketing, digital marketing channels have been expanded, and marketing content and formats have been continuously innovated, attracting a large number of tourists [15]. Most importantly, the construction of smart tourism systems and the application of digital technologies have improved cultural tourism management and service levels, directly enhancing tourist experiences [16], [17]. These innovations based on digital technologies are driving the cultural tourism industry to undergo a transformative change, continuously revitalizing its vitality.

The accelerated development of digital technology has become a key driver for the transformation and upgrading of traditional tourism. Cultural tourism digitalization is a vivid example of the integration and mutual reliance of digital technology and the cultural tourism industry in the era of the experience economy. Cuomo, M. T., et al. examined tourism management design supported by data-driven decision-making methods. By analyzing social big data and user-generated content, decision-makers can be provided with better decision-making methods to enhance visitor experience value [18]. Marques, L. and Borba, C. integrated digital technology into urban tourism development, linking tangible and intangible culture to make tourism practices more interactive and engaging, thereby enhancing visitors' creative tourism experiences in cities [19]. Han, D. I. D. et al. explored the impact of virtual reality and augmented reality technologies on visitor experiences and designed enhanced tourist attractions integrating such participatory interactive technologies, enabling visitors to obtain high-value tourism experiences in cultural tourism contexts [20]. Stankov, U., and Gretzel, U., et al. demonstrated that traditional cultural tourism activities often lack visitor-centered experiential interactive design. Therefore, they utilized the tourism enhancement and system interaction functions of emerging Tourism 4.0 technologies to further enrich visitors' experiences in the cultural tourism process [21]. da Costa Liberato, P. M., et al. emphasized the importance of information and communication technology (ICT) in smart tourism destination management, noting that information transmitted via the internet serves as a critical data source for exploring visitor experiences and significantly influences the innovative development of tourism destinations [22]. Tussyadiah, I. P. also pointed out that ICT can assist tourism destinations in addressing design challenges while enhancing tourism experience value by influencing visitor behavior, benefiting all stakeholders [23].

This paper examines the extent to which digital technology influences the current development of the tourism industry, as well as the specific mechanisms and pathways involved, from the perspective of digital tourism. The study constructs an evaluation index system for cultural tourism experience innovation and industrial upgrading based on digital technology, and employs factor analysis models and the Tiel index to measure their development levels, with empirical analysis conducted using typical case studies. Subsequently, the development level of cultural tourism experience innovation based on digital technology is used as the core explanatory variable, industrial upgrading as the dependent variable, and relevant control variables are selected based on previous literature to construct an empirical regression model. The impact is empirically analyzed using panel data from 2013 to 2023.

II. Innovation in cultural tourism experiences and industrial upgrading based on digital technology

II. A. Measurement model for innovation in cultural tourism experiences based on digital technology

II. A. 1) Construction of an evaluation indicator system

The evaluation indicator system for cultural tourism experiences based on digital technology encompasses a wide range of content, and its development process is relatively complex. It is nearly impossible to fully capture the rich connotations of this concept using only a few indicators. Therefore, to provide a more comprehensive interpretation of this concept, it is necessary to establish a comprehensive indicator system and a scientific evaluation method. After reviewing a significant number of relevant literature, and considering the current state of innovation in digital-based cultural tourism experiences, as well as objective factors related to data, 10 indicators were selected. Table 1 presents the composition of the evaluation indicator system for digital-based cultural tourism experience innovation.

Table 1: Metric system composition

Index name
Monthly income/living expenses (x1)
Understand the pathway (x2)
Travel relationship (x3)
Pay square (x4)
Like digital technology travel service (x5)
Travel budget cap (x6)
Interested areas of tourism (x7)
Consumer applications (x8)
The lack of digital tourism (x9)
Interested digital technology projects (x10)

II. A. 2) Factor analysis measurement model

(1) Mathematical model of factor analysis

The mathematical model of factor analysis [24] assumes that there are p original variables, which are denoted by $X_1, X_2, ..., X_p$, respectively. To reduce the dimensionality of the data, we represent each original variable as a linear combination of $k(k < p)$ factors $F_1, F_2, \ldots, F_k$, i.e.:

$$\begin{cases} X_1 = a_{11}F_1 + a_{12}F_2 + a_{13}F_3 + \ldots + a_{1k}F_k + \varepsilon_1 \\ X_2 = a_{21}F_1 + a_{22}F_2 + a_{23}F_3 + \ldots + a_{2k}F_k + \varepsilon_2 \\ X_3 = a_{31}F_1 + a_{32}F_2 + a_{33}F_3 + \ldots + a_{3k}F_k + \varepsilon_3 \\ \vdots \\ X_P = a_{P1}F_1 + a_{P2}F_2 + a_{P3}F_3 + \ldots + a_{Pk}F_k + \varepsilon_P \end{cases} \tag{1}$$

(2) Related concepts in factor analysis

An important concept in factor analysis is variable commonality, also known as common variance. In factor analysis, by calculating variable commonality, we can better understand the relationship between variables and factors and select appropriate factors for data dimensionality reduction.

In factor analysis, the variance contribution of a factor refers to the sum of the squares of the elements in the i th column of the factor loading matrix, which is used to measure the explanatory power of the j th factor on the total variance of the original variables. The higher this value, the stronger the explanatory power of the corresponding factor and the greater its contribution to the data. Therefore, the variance contribution of a factor is an important indicator that helps us select the most representative and explanatory factors, thereby better understanding the structure and characteristics of the data.

(3) Basic Steps of Factor Analysis

First, certain prerequisites must be met to perform factor analysis. During the analysis and testing process, the following methods can be used:

The first method is the correlation coefficient matrix screening method: by analyzing the correlation coefficient matrix between variables, if most of the correlation coefficients are less than 0.3, these variables are not suitable for factor analysis. This method can effectively exclude variables that contribute little to the factor analysis results, thereby improving the accuracy and reliability of the analysis.

The second method is the transposed correlation matrix: the off-diagonal elements are equal to the negative values of the partial correlation coefficients; the diagonal elements are calculated using the following formula:

$$MSA_i = \frac{\sum_{j \neq i} r_{ij}^2}{\sum j \neq i r_{ij}^2 + \sum j \neq i p_{ij}^2} \tag{2}$$

The third method is Bartlett's sphericity test. Starting from the correlation coefficient matrix of the original variables, assuming that the correlation coefficient matrix is the identity matrix, if the corresponding p-value of the test is less than the given significance level α, the original assumption should be rejected, and the original variables are considered suitable for factor analysis.

The fourth method is the KMO test. This statistic ranges from 0 to 1, with values closer to 1 indicating stronger correlations between variables, making the original variables suitable for factor analysis. Values above 0.9 indicate very suitable; 0.8–0.9 indicate suitable; 0.7–0.8 indicate generally suitable; 0.6–0.7 indicate somewhat suitable; 0.5–0.6 indicate not very suitable; and values below 0.5 indicate extremely unsuitable.

To ensure more accurate test results, this study employed two validation methods—Bartlett's sphericity test and KMO test—to verify the correlation between variables. SPSS software was used for calculations, simplifying the computational workload while yielding more persuasive results.

The second step is to extract factors based on the suitability of factor analysis in the first step.

The factor loading matrix is generally solved using the principal component method. Principal component analysis transforms the original p variables into a new set of uncorrelated variables Y through coordinate transformation and linear combination, i.e.:

$$\begin{cases} Y_1 = u_{11}X_1 + u_2X_2 + u_3X_3 + \ldots + u_{1p}X_p \\ Y_2 = u_{21}X_1 + u_{22}X_2 + u_{23}X_3 + \ldots + u_{2p}X_p \\ Y_3 = u_{31}X_1 + u_{32}X_2 + u_{33}X_3 + \ldots + u_{3p}X_p \\ \vdots \\ Y_p = u_{p1}X_1 + u_{p2}X_2 + u_{p3}X_3 + \ldots + u_{pp}X_p \end{cases} \tag{3}$$

$$u_2i_1 + u_2i_2 + u_2i_3 + \ldots + u_2i_p = 1(i = 1, 2, \ldots, p) \tag{4}$$

The variables determined according to the above principles are the first, second, third, ... pth principal components of the original variables, respectively. Among these, the first principal component accounts for the largest proportion of the total variance, while the proportions of the remaining principal components in the total variance decrease successively, meaning that the ability of the principal components to summarize the original variables decreases successively.

There are three methods for determining the number of factors: first, the number of factors can be determined based on the eigenvalues, generally selecting eigenvalues greater than 1; second, the number of factors can be determined based on the specified number of roots and the eigenvalue scatter plot, and by observing the scatter plot, the number of factors can be determined based on the boundary between steep and gentle slopes; finally, the number of factors can be determined based on the cumulative variance contribution rate of the factors. The third step is to make the factors interpretable.

When multiple factors have large values in the jth column of the factor loading matrix, the meaning of factor F_j is often unclear. To address this issue, factor rotation is typically used to ensure that a variable value has high loadings on as few factors as possible. Factor rotation generally employs orthogonal rotation, which ensures that the newly generated variables remain uncorrelated. The method of maximum variance is a common orthogonal rotation method. After factor rotation, the factors should be named based on their explanatory power for the original variables to better understand and interpret the results of factor analysis.

$$F_j = w_{j1}X_1 + w_{j2}X_2 + w_{j3}X_3 + \ldots + w_{jp}X_p \quad (j = 1,2,3,\ldots,k) \tag{5}$$

II. B.Industrial upgrading measurement model

II. B. 1) Construction of an industrial upgrading evaluation index system

After determining the new connotation of industrial upgrading, this paper comprehensively reviews the research results of previous scholars and follows the principles of scientificity, comparability, and completeness of the indicator system. At the same time, considering the availability of indicator data, an industrial upgrading measurement indicator system is constructed, as shown in Table 2. The first-level indicators represent the overall industrial upgrading status, the second-level indicators represent the current status of each industrial upgrading, and the third-level indicators represent the indicator layer.

Table 2: Industrial upgrade measure system

Primary indicator	Secondary indicator	Tertiary index
Industrial upgrade	The first production industry upgraded	The output of the first production
		The number of jobs in the first production industry
	The second production industry upgraded	The output of the second production
		The number of jobs in the second production industry
	The third production industry upgraded	The output of the third production
		The number of jobs in the third production industry

II. B. 2) Construction of the Industrial Upgrade Index

Based on the above-mentioned indicator system, most scholars often use entropy values and comprehensive evaluation methods to assign weights to indicators at various levels and conduct comprehensive evaluations. This paper draws on previous methods for constructing industrial upgrading measurement indices and uses the Theil index [25] to construct a comprehensive industrial upgrading index, namely the industrial rationalization index. The specific calculation formula is as follows:

$$TL = \sum_{i=1}^{n}\left(\frac{Y_i}{Y}\right)\ln\left(\frac{Y_i}{Y}\times\frac{L_i}{L}\right) \tag{6}$$

In Formula (6), Y_i represents the output of the i th industry in a prefecture-level city, and Y represents the total output of all industries in a prefecture-level city; L_i represents the number of employed persons in the i th industry in a prefecture-level city, and L represents the total number of employed persons in all industries in a prefecture-level city. Furthermore, according to Formula (6), the TL indicator value ranges from 0 to 1. A smaller TL value indicates a more reasonable industrial structure, with various industries and sectors tending toward high-quality, high-value-added development; conversely, a larger TL value suggests that the industrial structure is gradually deviating from an optimal state, with certain issues existing in the development of various industries and sectors.

II. C.Measurement of Cultural Tourism Experience Innovation and Industrial Upgrading

II. C. 1) Measurement of Cultural Tourism Experience Innovation

(1) Standardization of indicators

The selected indicator variables in this paper differ in terms of dimensions and units of measurement. Therefore, Z-score standardization was used to standardize the selected indicators.

(2) Correlation analysis of indicators

The higher the correlation coefficient, the stronger the correlation, indicating the degree of association between the various characteristics of the selected indicators. Among them, the correlation coefficient between “aspects of travel that interest you” and “digital technology projects that interest you” is 0.48, indicating the strongest correlation. The correlation coefficient between “monthly income/living expenses” and “maximum budget for travel” is 0.44, ranking second in strength. The correlation between “payment methods” and “digital technology travel services” ranks third, with a correlation coefficient of 0.33. The correlations between the remaining indicators are relatively weak.

(3) Factor Analysis

1) Determining the Number of Factors

Figure 1 shows the scree plot and cumulative contribution rate plot. It can be seen that the scree plot begins to flatten after three points, so three common factors are extracted. The eigenvalues of the first three factors are all greater than 1, at 2.978, 1.781, and 1.312, respectively, with a cumulative contribution rate of 60.71% > 60%, which is sufficient to explain all variables.

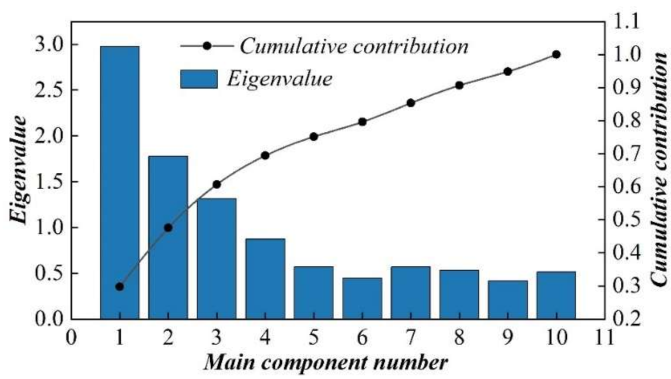


Figure 1: The composite diagram and the cumulative contribution ratio

2) Factor loading matrix

This paper uses the maximum variance rotation method for factor rotation. The factor loading matrix is shown in Table 3, which shows the factor loading matrix after rotation. The first principal factor has high loadings for X3 and X4, the second principal factor has high loadings for X1 and X6, and the third principal factor has high loadings for X7 and X8. Through factor analysis, three common factors were extracted from the 10 indicators and named as digital tourism, financial planning, and digital experience.

Table 3: Factor load matrix

Index name	Factor1	Factor2	Factor3
Monthly income/living expenses (x1)	0.15073	0.8247	-0.14771
Understand the pathway (x2)	0.69321	0.06001	0.23809
Travel relationship (x3)	0.7172	-0.02803	0.05782
Pay square (x4)	0.76027	-0.04382	0.03462
Like digital technology travel service (x5)	0.64017	0.17589	0.15171
Travel budget cap (x6)	-0.08472	0.84613	0.15374
Interested areas of tourism (x7)	0.05984	-0.00652	0.81386
Consumer applications (x8)	0.13012	0.02515	0.80178
The lack of digital tourism (x9)	0.21741	0.02617	0.70666
Interested digital technology projects (x10)	0.44954	-0.07876	0.39899

3) Factor score model

Using linear regression, we obtain the formula for calculating the factor score:

$$\begin{aligned} F_1 &= 0.15073x_1 + 0.69321x_2 + \ldots + 0.21741x_9 + 0.44854x_{10} \\ F_2 &= 0.8247x_1 + 0.06001x_2 + \ldots + 0.02617x_9 - 0.07876x_{10} \\ F_3 &= -0.14771x_1 + 0.23809x_2 + \ldots + 0.70666x_9 - 0.39899x_{10} \end{aligned} \tag{7}$$

Weighting is performed using the ratio of the main factor variance contribution rate to the cumulative contribution rate, and the weighted sum is calculated to obtain the following factor score model:

$$F = 25.22F_1 + 18.61F_2 + 16.88F_3 \tag{8}$$

The main factor F1 has a relatively large coefficient, indicating that the development of digital tourism has a significant impact on the innovation of cultural tourism experiences. The second factor is financial planning factor F2, which, although not as influential as the digital tourism development factor, represents an individual's economic status and is a key factor in cultural tourism. The remaining factors have a relatively weak impact on the innovation of cultural tourism experiences.

II. C. 2) Measurement of industrial upgrading

(1) Calculation of the industrial upgrading index

This paper uses data from 30 provinces in China (excluding the Tibet Autonomous Region) from 2013 to 2023 to calculate China's industrial upgrading index. Economic data has been deflated using the Consumer Price Index (CPI) with 2013 as the base year. The data sources include the China Regional Economic Database, China Energy Database, China Environmental Database, China Science and Technology Database, and China National Knowledge Infrastructure (CNKI) Statistical Data Platform from the EPS Global Data Statistics Platform. For missing data, this paper primarily employs interpolation and moving average methods to fill in the gaps. Due to formatting constraints, only the industrial upgrading indices for the years 2013, 2018, and 2023 are analyzed here. Table 4 presents the industrial upgrading indices and rankings for each year.

The industrial upgrading indices of Beijing, Shanghai, and Tianjin have consistently ranked first, second, and third, respectively, in representative years. By 2023, their industrial upgrading indices will all exceed 0.81, far surpassing those of other provinces, municipalities, and autonomous regions. This indicates that the industrial development of Beijing, Shanghai, and Tianjin is relatively well-developed, providing favorable conditions for industrial transformation and upgrading. Following closely behind are Zhejiang, Jiangsu, and Guangdong provinces, which rank fourth, fifth, and sixth, respectively. These three provinces are located in the economically developed eastern region of China, with relatively well-developed industrial structures and competitive advantages in their respective specialty industries, providing sufficient momentum for industrial upgrading. Hubei, Chongqing, Sichuan, and Guizhou saw steady improvements in their industrial upgrading levels during the representative years. Sichuan and Hubei saw significant increases, both ranking among the top 10. Hubei's progress is closely related to the province's ongoing efforts to upgrade traditional industries and develop emerging industries in recent years. Although the pandemic had a significant impact on Hubei Province's economy and other aspects, Wuhan City's GDP ranked 11th in the first half of 2020, although it fell out of the top 10, this is still a commendable achievement. This is closely tied to Wuhan City's vigorous development of high-tech industries such as semiconductors, biopharmaceuticals, display panels, and aerospace. Meanwhile, western regions such as Guizhou, Gansu, Ningxia, and Xinjiang, which are relatively economically underdeveloped, rank at the bottom in terms of industrial upgrading levels.

Table 4: Industry upgrade index and ranking

Region	2013	Rank	2018	Rank	2023	Rank
Beijing	0.762	1	0.848	1	0.908	1
Tianjin	0.652	3	0.777	2	0.815	3
Hebei	0.474	15	0.572	16	0.656	13
Shanxi	0.354	26	0.507	24	0.594	24
Inner Mongolia	0.393	21	0.536	21	0.602	23
Liaoning	0.501	13	0.628	10	0.644	17
Jilin	0.492	12	0.586	12	0.627	20
Heilongjiang	0.5	11	0.582	14	0.647	18
Shanghai	0.708	2	0.761	3	0.824	2
Jiangsu	0.617	5	0.728	5	0.799	4
Zhejiang	0.617	4	0.724	4	0.793	5
Anhui	0.491	14	0.569	17	0.649	15

Fujian	0.554	7	0.657	7	0.737	7
Jiangxi	0.537	9	0.586	11	0.675	12
Shandong	0.538	8	0.646	8	0.738	8
Henan	0.462	18	0.566	19	0.636	19
Hupei	0.461	17	0.583	13	0.695	10
Hunan	0.478	16	0.549	20	0.643	16
Guangdong	0.581	6	0.67	6	0.764	6
Guangxi	0.352	25	0.524	23	0.617	21
Hainan	0.517	10	0.645	9	0.663	11
Chongqing	0.391	22	0.562	18	0.656	14
Sichuan	0.445	19	0.572	15	0.693	9
Guizhou	0.137	30	0.417	29	0.567	25
Yunnan	0.367	23	0.464	26	0.563	26
Shaanxi	0.399	20	0.526	22	0.61	22
Kansu	0.302	28	0.461	27	0.536	29
Qinghai	0.338	27	0.46	25	0.564	27
Ningxia	0.178	29	0.394	30	0.504	30
Xinjiang	0.361	24	0.442	28	0.525	28

(2) Dynamic Evolution Analysis of Industrial Upgrading

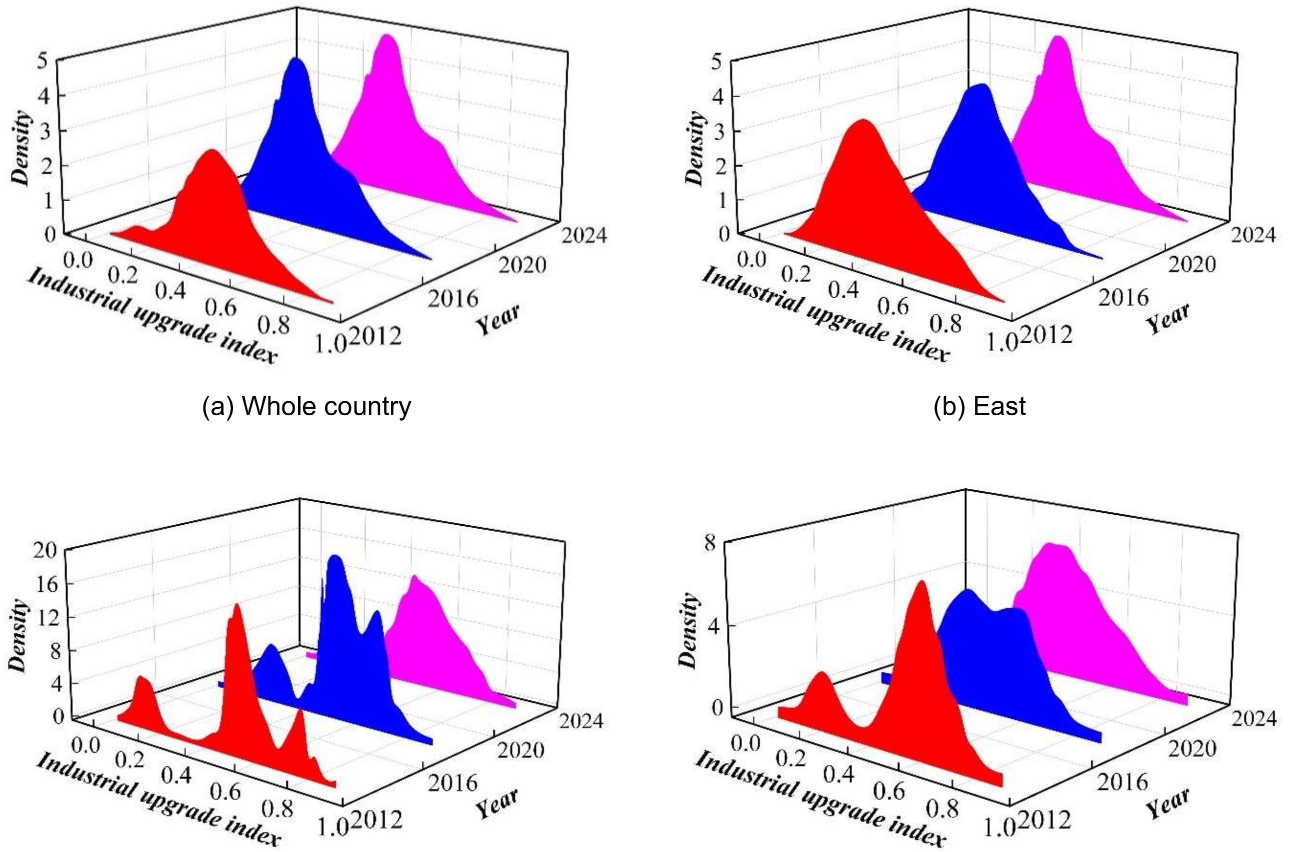
Based on the calculated industrial upgrading index, this paper further analyzes the dynamic evolution process of China's industrial upgrading using kernel density estimation. The kernel density estimates of industrial upgrading in China and its various regions are shown in Figure 2.

Figure (a) provides an overall description of the national industrial upgrading development process, displaying the kernel density estimation curves for the years 2013, 2018, and 2023. As shown in Figure (a), over time, China's industrial upgrading kernel density curve has steadily shifted to the right, transitioning from nearly a normal distribution to a slightly right-skewed distribution, indicating that China's overall industrial upgrading development level is steadily improving. At the same time, the steepness of the kernel density curve has increased, indicating that the distribution of industrial upgrading levels among provinces in China has become increasingly concentrated. It can also be observed that China's industrial upgrading kernel density curve has gradually shifted from a bimodal distribution to a unimodal distribution and then back to a bimodal distribution, indicating that the gap in industrial upgrading levels among provinces in China has gradually widened, and the trend of a two-tiered industrial upgrading level has gradually become more pronounced.

As can be seen from Figure (b), the nuclear density curve in the eastern region shifted to the right at the fastest rate, and the nuclear density curves for the three years were most similar in shape. This may be because the eastern region is mostly economically developed, providing a favorable environment for industrial upgrading and abundant resources. At the same time, the nuclear density curve in the eastern region is basically normally distributed, indicating that the level of industrial development in the eastern region is relatively uniform.

It can be seen from Figure (c) that the kernel density curve in the central region gradually changed from a three-peak distribution to a bimodal distribution, and the height of the peaks decreased significantly, indicating that the gap between provinces in the central region was gradually narrowing. This may be due to the implementation of the strategy of the rise of the central region and the inclination of relevant national policies, which has continuously strengthened the economic strength of the central region and promoted the transformation of traditional manufacturing to high-quality manufacturing.

As can be seen from Figure (d), the industrial upgrading kernel density curve in the western region gradually shifts from a bimodal distribution to a unimodal distribution, and from a peak distribution to a flattened distribution. That is, the level of industrial development in the western region gradually shifts from a polarized distribution to a unipolar distribution, and the gap between provinces gradually narrows. This indicates that the level of industrial upgrading in both regions has improved overall, which may be related to the improvement in the economic strength of each region.



(a) Whole country (b) East

(c) Middle (d) West

Figure 2: Estimates of the nuclear density of industrial upgrading in China and regions

III. Empirical Research on the Impact of Cultural Tourism Experience Innovation on Industrial Upgrading

III. A. Construction of measurement models

The econometric model constructed in this chapter is as follows:

$$\ln ia = \beta_0 + \beta_1 \ln ct + \beta_2 \ln fdi + \beta_3 \ln la + \beta_4 \ln sc + \beta_5 \ln lop + \mu + \varepsilon \tag{9}$$

The dependent variable of the model is a factor reflecting the evolution and rationalization of industrial structure. β_0 is the intercept term, fdi is foreign direct investment, la is factor endowment, sc is technological input, and lop is the level of financial development. ct is the composite variable for cultural tourism experience innovation based on digital technology, μ represents the individual fixed effects of provinces that do not change over time, and ε represents the random disturbance term, which follows an independent and identically distributed distribution.

III. B. Variable Selection and Data Sources

III. B. 1) Dependent variables

This paper examines the factors influencing industrial upgrading. Chapter 2 of this paper provides a detailed description of these factors, so this chapter will not go into further detail. In the following text, ia will be used as the dependent variable.

III. B. 2) Core explanatory variables

This paper draws on the relevant research and measurement analysis of indicators related to “digital technology-based cultural tourism experience innovation” from the aforementioned literature. It employs factor analysis to process data on the ten indicators of “digital technology-based cultural tourism experience innovation” in China.

Finally, these indicators are used as the basic explanatory variables for empirical analysis. This paper constructs the indicators for innovation in cultural tourism experiences based on digital technology from three aspects: digital tourism, financial planning, and digital experiences. The specific selection of indicators and data calculation for measuring the development level of "innovation in cultural tourism experiences based on digital technology" in China are not repeated here.

III. B. 3) Control variables

(1) Foreign Direct Investment (FDI)

Since the reform and opening-up, China has not only entered the process of globalization but has also strived to achieve a mutually beneficial situation of learning from foreign countries. In this process, foreign mature management experience and scientific and technological achievements have gradually entered China. As a result, China's economic development, industrial development level, and production efficiency have been profoundly influenced. In this paper, FDI not only brought research and development funds to China but also enhanced corporate technological capabilities and technical talent, thereby elevating industrial standards. Additionally, FDI selectively participated in China's economic activities, driving the rise and fall of various industries. Therefore, this paper selects FDI as a control variable to analyze the impact of innovation in cultural tourism experiences based on digital technology on industrial upgrading. It concludes that foreign direct investment has a positive impact on industrial upgrading.

(2) Factor endowment

According to economic theory, factor endowment refers to the quantity of various production factors (including land, labor, capital, and entrepreneurial ability) that a country possesses and can use for production. For a long time, high-tech talent has been able to bring significant technological progress and breakthroughs, as well as notable economic growth and social development, to a country in the present and over the next decade or even century. Therefore, it plays a crucial role in the optimization and upgrading of industrial structure. Currently, China is undergoing a phase of continuous transformation from an extensive to an intensive industrial structure. High-tech talent plays a significant role in promoting China's economic transition from high-speed to high-quality development. Therefore, to more comprehensively reflect the influence of various factors, this paper selects the proportion of high-tech personnel as an indicator to measure factor endowment. This paper concludes that factor endowment has a positive impact on industrial upgrading.

(3) Technological Investment

The level of technological development achieved through a country's investment in technology often determines the improvement of its production capacity and international competitiveness, enabling its products to advance to higher segments of the global value chain. Therefore, technological investment is crucial for industrial optimization and upgrading. This paper selects scientific expenditure (SC) as the variable to measure technological investment. Scientific expenditure refers to a country's fiscal spending on research and development and the promotion of scientific innovation. This investment is primarily reflected in the cultivation of scientific research personnel and project funding. Therefore, this variable not only measures current innovation and R&D investment but also indirectly reflects a country's emphasis on science and technology, theoretical research, and scientific education, all of which contribute to a country's future technological and talent reserves. This paper argues that technological investment has a positive impact on industrial upgrading.

(4) Level of financial development

Traditional financial institutions and internet-based financial institutions primarily influence and support business development through the borrowing and lending of funds. Since finance provides capital support for business operations, it not only expands the scope of business activities but also generates revenue. Additionally, scientifically sound financial development can invest in high-tech industries with promising prospects, higher production efficiency, and better product quality, as well as enterprises with comparative advantages in various fields, thereby promoting their growth and acquisition of international market share. Based on scientific assessments and rational judgments about future development, financial investment not only optimizes the allocation of social resources and enhances efficiency but also drives industries toward higher levels of development and more rational directions. Therefore, using the ratio of financial institution loans to GDP (LOP) as a measure, this paper argues that the level of financial development has a positive impact on industrial upgrading.

III. B. 4) Data Sources

This study focuses on the innovation level index of cultural tourism experiences based on digital technology, conducting research and analysis from 20013 as the base year up to 2023. The study selected 30 provinces in China as samples and utilized data from the "Indicators for Digital Economy and Industrial Structure Upgrading," which primarily sourced from the "China Science and Technology Statistical Yearbook" and the "China Urban

Statistical Yearbook." The original financial indicators were obtained from the "China Financial Statistical Yearbook," while the remaining variables were derived from the aforementioned statistical reports and directories.

III. C. Empirical regression results and analysis

III. C. 1) Multiple collinearity test

Since the variables selected in this paper are all at the macro level, there may be strong correlations between them, potentially leading to multicollinearity issues that could hinder accurate model estimation. Therefore, this section conducts multicollinearity tests on the data to ensure the reliability of subsequent regression results. Table 5 presents the analysis of variable correlation coefficients. It can be observed that some variables exhibit strong correlations, such as the coefficient between la and ia reaching 0.771. However, relying solely on correlation coefficients cannot accurately determine the presence of multicollinearity issues. Therefore, this paper further examines the variance inflation factor of the variables.

The dependent variable of the model reflects the evolution and rationalization of the industrial structure. β_0 is the intercept term, fdi represents foreign direct investment, la represents factor endowments, sc represents technological input, and lop represents the level of financial development. ct is the composite variable for cultural tourism experience innovation based on digital technology, μ represents the individual fixed effects of provinces that do not change over time, and ε represents the random disturbance term, which follows an independent and identically distributed distribution.

Table 5: Analysis of variable correlation coefficients

	ia	fdi	la	sc	lop	ct
ia	1.000					
fdi	0.598***	1.000				
la	0.771***	0.585***	1.000			
sc	-0.069	-0.388***	-0.522***	1.000		
lop	0.762***	0.688***	0.865***	-0.383***	1.000	
ct	0.094	0.161**	0.033	-0.195***	0.005	1.000

Table 6 shows the results of the variance inflation factor (VIF) statistics. The VIF value for each variable is less than 10, and the average VIF value is 4.08. Therefore, it can be concluded that there is no multicollinearity issue.

Table 6: Variance inflation factor statistics

Variable name	VIF	1/VIF
fdi	2.22	0.45
la	8.85	0.11
sc	1.78	0.56
lop	6.45	0.16
ct	1.12	0.89
Mean VIF	4.08	

III. C. 2) Benchmark regression results

Table 7 presents the basic regression results for the three models: the mixed-effects model (POLS), the fixed-effects model (FE), and the random-effects model (RE). Columns (1) and (2) show the mixed regression results with and without control variables, respectively, while columns (3) and (4) present the fixed-effects model regression results with and without control variables, respectively. Columns (5) and (6) present the regression results for the random effects model with and without control variables, respectively. As can be seen, the coefficients of the core explanatory variables are all significantly positive across the three regression models. Since the data in this study are in short panel form, both the fixed effects model and the random effects model can be used. Therefore, this study employs the Hausman test, whose results strongly reject the null hypothesis, leading to the selection of the fixed effects model.

As shown in Column (3), when considering only the core explanatory variables, their coefficients are significantly positive at the 5% level, indicating that cultural tourism experience innovations based on digital technology have a positive promotional effect on regional industrial structure upgrading. Column (4) includes a series of control variables that may influence regional industrial upgrading, such as foreign direct investment (fdi), factor endowments (la), technological inputs (sc), and financial development levels (lop), among others. The impact coefficient is 0.185 and is significantly positive at the 5% level. The economic implication is that for every 1-unit increase in the cultural tourism experience innovation development index based on digital technology, the regional industrial upgrading index increases by 0.185 units. This suggests that cultural tourism experience innovation based on digital technology drives the gradual evolution of the regional industrial structure from the primary sector toward the secondary and tertiary sectors. The underlying reason may be that the technological innovations and human capital mobility resulting from cultural tourism experience innovation based on digital technology have played a catalytic role in industrial structure upgrading.

Table 7: The impact of cultural tourism experience on industrial upgrading

Explained variables: industrial upgrade (ia)						
Variable name	POLS		FE		RE	
	(1)	(2)	(3)	(4)	(5)	(6)
ct	0.518*** (6.11)	0.225*** (3.38)	0.491** (3.52)	0.185** (2.11)	0.494*** (3.52)	0.192** (2.18)
fdi		0.822*** (8.25)		0.885*** (4.42)		0.844*** (5.52)
la		0.279*** (12.56)		0.255*** (1.55)		0.291*** (5.52)
sc		0.005 (0.25)		0.011 (0.21)		0.021 (0.62)
lop		0.241*** (4.21)		0.283*** (3.08)		0.288*** (3.33)
Time fixed effect	NO	NO	YES	YES	NO	NO
Provincial fixation effect	NO	NO	YES	YES	NO	NO
Constant term	2.351*** (233.58)	1.622*** (18.11)	2.333*** (122.41)	1.582*** (3.99)	2.348*** (105.58)	1.515*** (4.48)
R2	0.383	0.788	0.383	0.784	0.383	0.786

III. C. 3) Endogeneity treatment

This paper conducts an exogeneity test on the core explanatory variable of cultural tourism experience innovation based on digital technology. The p-values of the Durbin and Wu-Hausman tests are both 0, strongly rejecting the null hypothesis that the explanatory variable is exogenous. Therefore, this paper adopts the instrumental variables method to address the endogeneity issue. The number of fixed-line telephone users in each province is crossed with the number of internet broadband access users from the previous year (time-dependent) to form an interaction term, which serves as the instrumental variable for the level of digital trade development in that region for that year. Table 8 presents the regression results of the endogeneity test.

Columns (1) and (2) of the table report the results of the two-stage least squares (2SLS) regression using the aforementioned instrumental variables. The regression coefficient is 0.882 and passes the 1% significance test, indicating that digital trade does indeed promote regional industrial upgrading. Additionally, the weak instrumental variable test results show that the Cragg-Donald Wald F statistic is 28.561, rejecting the hypothesis of weak instrumental variables, and the Kleibergen-Paap rk LM statistic is 25.231, with a p-value of 0, indicating that the hypothesis of insufficient instrument identification is rejected. The Hansen J test results have a p-value of 0, rejecting the null hypothesis of over-identification. Therefore, the selection of the instrumental variables is reasonable and appropriately identified.

In addition to using historical data as instrumental variables, this paper selects the lagged value of the Digital Trade Development Index as instrumental variables in columns (3) and (4) and employs the Generalized Method of Moments (GMM) method for regression. This instrumental variable is both correlated with the current level of digital trade development and satisfies the exogeneity requirement. The regression results are shown in the table. The impact of digital trade on industrial upgrading remains significantly positive and has passed the weak instrumental variable and identification tests (Cragg-Donald Wald F statistic = 1259.338, Kleibergen-Paap rk LM statistic = 8.159, p-value = 0.005, Hansen J test p-value = 0).

Table 8: Endogenous test regression results

	2SLS		GMM	
Variable name	(1) ct	(2) ia	(1) ct	(2) ia
ct		0.882*** (4.25)		0.158*** (2.58)
iv	0.135*** (5.15)		1.055*** (20.01)	
fdi	-0.828*** (-3.18)	0.834*** (3.95)	-0.056 (-0.78)	0.981*** (5.55)
la	0.042 (0.18)	0.061 (0.44)	0.105*** (2.88)	0.123 (0.85)
sc	0.155*** (3.22)	-0.165** (-2.51)	0.051 (3.11)	0.000 (0.00)
lop	-0.171** (-2.52)	0.438*** (5.51)	0.005 (2.75)	0.282*** (4.41)
Time fixed effect	YES	YES	YES	YES
Provincial fixation effect	YES	YES	YES	YES
R2	0.611	0.411	0.952	0.645

IV. Conclusion

This study adopts a perspective of cultural tourism experience innovation based on digital technology to conduct targeted modeling of the current state of industrial optimization. Factor analysis is employed to assess the impact of cultural tourism experiences on industrial optimization within the region. Based on the aforementioned conclusions, and against the backdrop of digital economic development, this study collects panel data to advance empirical analysis, focusing on the specific forms and pathways through which technology influences industrial optimization. The following conclusions are drawn:

For every 1-unit increase in the cultural tourism experience innovation development index based on digital technology, the regional industrial upgrading index increases by 0.185 units, indicating that cultural tourism experience innovation based on digital technology drives the gradual evolution of the region's industries from the primary sector to the secondary and tertiary sectors. Additionally, two instrumental variables were selected and analyzed using two-stage least squares and generalized method of moments estimation to address the inevitable endogeneity issue, confirming that technological innovation can effectively promote industrial upgrading.

Therefore, it is essential to accelerate the digital transformation of traditional industries, promote the integration and innovation of traditional technologies such as manufacturing, energy, and biotechnology with digital technology, and expedite the development and application of new technologies like smart manufacturing, information materials, and biosensing to achieve a revolutionary breakthrough in the digitalization of manufacturing. More importantly, it is crucial to advance the digitalization of the tertiary sector, including industries such as online education, smart healthcare, intelligent logistics, digital inclusive finance, and digital public services. By leveraging digital technology to accelerate development in these areas, we can better meet consumers' personalized demands for products and services.

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