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## Article

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## DIGITAL CULTURE AND TOURISM: PERCEPTION OF LANDSCAPE CULTURE AND DISTRIBUTION OF HOMESTAY

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### Abstract

This research explores how landscape cultural perception impacts the spatial distribution of homestay businesses, and highlights the increasing role of digital technology in enhancing cultural tourism experiences and optimizing homestay industry operations. Using grounded theory, the research gets a relationship matrix to explore the theoretical logic between landscape resources and cultural perceptions, and then based on the S-O-R model, a theoretical framework is constructed to explain the impact of landscape culture perception on the distribution of homestays. The research also applies an empirical approach to analyse how cultural perceptions of landscape play in shaping the homestay distribution in Yangtze River Delta China. Additionally, digital platforms are found to enhance tourists' cultural perceptions and streamline their booking experiences, while providing homestay operators with effective tools for personalised marketing and operational efficiency.

**Keywords:** digital culture and tourism, spatial distribution of homestays, perception of landscape culture, traffic accessibility, digital platform, grounded theory, ridge regression.

**JEL Classification:** R12. Z32. C21

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## Introduction

In recent years, the global tourism market has exhibited robust recovery momentum. For example, Iceland has successfully attracted a significant number of tourists by promoting its unique image as the "Land of Fire and Ice," using its distinctive natural landscapes such as the Northern Lights and volcanic hot springs, which have established it as a world-renowned tourist destination (Röslmaier & Ioannides, 2023). Similarly, other tourist hotspots, such as the "Snow Festival" in Hokkaido, Japan, and the "Arctic Light Tour" in Finland, have capitalised on their unique cultural and natural resources to captivate global tourists, driving substantial growth in related industries (Nakayama, 2024; Inkinen et al., 2024). Alongside the flourishing tourism sector, supporting industries such as accommodation, dining, and other services have experienced rapid expansion (Ivanov & Webster, 2007; Andereck et al., 2005). Among these, the homestay sector, characterized by its personalized services and strong local cultural elements, has emerged as a significant form of tourism globally. Research has shown that the booming homestay industry can effectively stimulate local economies and promote synergies with related industries (Jamal et al., 2011). In regions rich in cultural and tourism resources, homestay clusters have become one of the most dynamic forms of tourism spatial organization (Guttentag et al., 2017). Globally, multiple cross-regional homestay clusters have emerged, such as Napa Valley in California, Provence in France, and Tuscany in Italy (Jones et al., 2015; Van et al., 1996). These regions have successfully used local cultural resources and unique natural conditions to attract a large numbers of tourists, fostering the development of housing clusters.

However, there are still many issues worthy of in-depth exploration. Currently, research on the internal relationship between tourism and homestays, especially the impact mechanism of different landscape cultural perceptions on the distribution of accessibility of homestays and the role of transportation in this process, remains relatively limited. Furthermore, with the widespread application of digital technology in the tourism field, it has had a profound impact on the tourism and homestay industries. Digital platforms not only provide tourists with rich cultural information, helping them better understand the cultural connotations of tourist destinations and enhancing their cultural awareness, but also simplify the booking process, allowing tourists to arrange their trips more conveniently. For homestay operators, digital platforms offer an effective way to personalized marketing. Through technical means such as big-data analysis, they can accurately grasp tourists' needs, develop targeted marketing strategies, and at the same time improve operational efficiency and reduce operating costs.

This research has made important contributions in many aspects. First, it is the first to systematically classify and quantify landscape cultural perceptions, construct a brand-new theoretical framework, and provide a systematic and scientific method for understanding the relationship between landscape resources and cultural perceptions. Through empirical research, the association between landscape cultural perceptions and homestay distributions has been revealed, enriching and improving the relevant theoretical system. Second, it provides practical insights for tourism professionals and managers, helping them better understand market demands, rationally plan homestay layouts, improve service quality, and promote the sustainable development of the cultural tourism and homestay industries.

## 1. Literature review

In the fields of tourism geography and economic geography, the spatial distribution relationship between homestays and tourist attractions has always been a major research issue. Past studies have clearly shown that homestays tend to cluster in areas rich in tourism resources, and their distribution is influenced by various factors such as the attractiveness of tourist attractions, accessibility to transportation, and the state of infrastructure. Many scholars have explored the spatial agglomeration effect of tourist attractions and homestays and found that in areas with important natural landscapes, homestays usually cluster around tourist attractions to improve tourists' convenience and experience. Moreover, the distribution of homestays does not solely rely on natural resources; local culture and social-economic conditions also have a significant impact on it (Qian et al., 2023). Taking the Yangtze River Delta China as an example, cities rich in cultural and tourism resources such as Hangzhou and Suzhou show a significant positive correlation between the number of homestays and the number of tourist attractions. Furthermore, transportation infrastructure such as roads, airports and railway stations has also been proven to be a key factor in influencing the distribution of homestays and tourist attractions (Zeng et al., 2024; Qian et al., 2023). However, existing studies mostly focus on the spatial relationship between natural attractions and homestays, paying relatively little attention to tourists' cultural perceptions of attractions.

The cultural shaping of tourist attractions plays a crucial role in the tourism industry. It not only directly determines the ability of attractions to attract tourists but also affects the distribution and types of nearby homestays (Guttentag et al., 2017; Huan et al., 2023; Wu and Chen, 2023). Many tourist attractions improve tourists' cultural experiences by excavating and displaying local cultural resources, such as historical relics, folk activities, and traditional architectural styles (Jamaludin et al., 2012). Successful cultural shaping often makes the cultural expressions of tourist attractions and homestays echo each other. As an important window for tourists to understand local culture, the cultural connotation of homestays is closely linked to that of attractions (KC and Thapa, 2024). In historical cities and UNESCO World Heritage sites, tourist attractions with profound cultural heritage are more likely to attract personalised high-end homestays (Qiao et al., 2021), and the depth of cultural shaping in these areas is closely related to the development model of homestays. However, there is a lack of research on quantifying tourists' cultural perceptions of attractions and exploring how these perceptions affect the distribution of homestays.

With the extensive penetration of digital technology in the tourism industry, the relationship between cultural shaping and the distribution of homestays has undergone profound changes (Li et al., 2024). Digital technology, through online cultural content and booking platforms, has greatly improved tourists' cultural awareness of tourist destinations (Goncalves et al., 2022). Current research shows that functions such as virtual tours and video demonstrations provided by digital tourism platforms can help tourists deeply understand the cultural background of destinations before departure, thus improving their cultural satisfaction after arrival (Chakravarty, 2024; Jia et al., 2024). At the same time, the emergence of online booking platforms such as Airbnb and Booking.com has completely changed the pattern of the homestay market, enabling hosts to use digital tools for precise marketing and service optimisation. Digital technology has also further promoted the interaction between the cultural shaping of tourist attractions and the distribution of homestays (Gupta, 2024).

In summary, first, although there has been a large amount of research on homestay distribution, cultural shaping of tourist attractions and the application of digital technology, the existing literature still has some fragmentation problems. Second, most studies focus on the relationship between homestays and natural tourist attractions, but the research on the interaction mechanism between the culture of tourist attractions and the distribution of homestays is not in-depth enough. Third, existing studies on the impact of digital technology on the tourism industry mostly focus on enhancing tourists' experiences, ignoring its in-depth impacts on perception of landscape cultural and distribution of homestays.

## 2. Theoretical framework

### 2.1. The classification of landscape cultural perception

Based on perceptions of historical and geographical cultural resources, tourists' perceptions of landscape culture can be categorized into four types: modern and humanities, ancient and nature, modern and nature, and ancient and humanities, as shown in Table no. 1.

**Table no. 1. Classification of tourists' perception of landscape culture**

Cultural perception classification		Geographical perception of cultural resources		Historical perception of cultural resources		Case
		Humanities	Nature	Ancient	Modern	
Geographical perception of cultural resources	Humanistic perception				<b>Modern Humanities:</b> Modern landscape produced by human influence after 1949.	Shanghai Science and Technology Museum, Tianyige Museum, etc.
	Natural perception			<b>Ancient Nature:</b> Ancient natural scenery that existed before 1949.		Xuedou Mountain, Suzhou Creek, etc.
Historical perception of cultural resources	Modern perception		<b>Modern Nature:</b> Natural scenery with modern characteristics was developed after 1949.			Century Park, Chenshan Botanical Garden, etc.
	Ancient perception	<b>Ancient Humanities:</b> Ancient landscape produced by human influence before 1949.				Lu Xun's hometown scenic spot, Chen Yun's former residence, etc.

## 2.2. The measurement of landscape cultural perception

Using the core concept of grounded theory and data from Ctrip's tourism website, along with user comments, Nvivo12 software is employed to construct the theoretical logic of the relationship between tourists' landscape resources and cultural perceptions, resulting in a relationship matrix that measures the degree of landscape cultural perception.

Two types of original texts were used: First, the introduction texts of scenic spots from Ctrip.com. A total of 6,250 introduction texts from 27 cities in the Yangtze River Delta region of China were extracted using Python software, and 5,659 effective samples were obtained after manual review and screening. Second, tourists' perception comments were collected. Based on the number of effective scenic spots in each city, 540 spots were selected as data for tourists' perception. Duplicate comments were excluded, and 1,569 valid perception comments were obtained. To ensure data quality, additional comments were collected from Qunar.com and TripAdvisor for triangulation.

### (1) Coding process

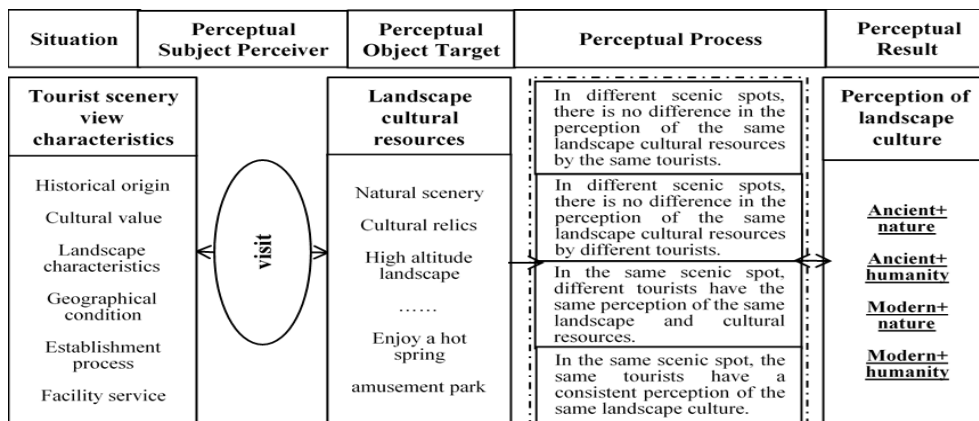
Following the grounded technology of procedural coding, this research utilizes Nvivo12 software for open coding, axial coding, and selective coding of scenic spot introductions and tourists' perception comments. This process of labeling, conceptualizing, and categorizing identifies relationships among several factors and constructs a theoretical model from the bottom up.

**Open coding.** Open coding involves conceptualizing data to form free nodes, preserving the original meaning of the text while eliminating less relevant nodes with fewer than three occurrences and merging those with similar meanings, forming 64 initial categories.

**Axial coding.** Axial coding is the process of inductively categorizing and constantly comparing to connect initial category codes together. This process involves selecting and constructing the content of main categories and linking primary conceptual categories with secondary ones to reorganize the data and establish logical relationships between the categories. The initial categories are synthesized to form 18 sub-categories and 6 main categories.

**Selective coding.** Selective coding, the third stage, extracts the core category and systematically analyzes its relationship with other categories in order to get the canonical relationship structure of the main categories. By comparing the categories formed through the three codes, the core category "Yangtze River Delta tourism landscape perception" is determined, and tourists' landscape perceptions are divided into two dimensions: historical resource perception and geographical resource perception.

Around the core category, a logical model of the relationship between tourists' perception of landscape resources and culture is constructed, as shown in Figure no. 1.



**Figure no. 1. The theoretical logic relationship between tourists' landscape resources and cultural perception on digital platform**

## (2) Saturation test

To test the theoretical saturation of the model, 20 recent tourist reviews were randomly obtained from Ctrip.com. Additionally, Nvivo12 software was used to search all coded samples. Results indicate that the key elements of tourists' landscape perception and their logical relationships are encompassed within the core category, and no new primary or secondary categories were identified, indicating the coding is approaching saturation. Four representative texts are provided as evidence.

Text 1: Moganshan Scenic Area, located west of Deqing County, Huzhou City, Zhejiang Province, covers an area of about 4 square kilometers. Major scenic spots include Jianchi, Qingliang Pavilion, Xuguangtai, Dicuitan, Dakeng, and Mogan Lake. The area boasts high forest coverage, with more than 180 peaks, the highest being Tashan at 720 meters above sea level. The scenic area also offers summer villas, resorts, and homestays, providing good options for viewing and accommodation during summer.

Text 2: The image of Bao Gong's impartiality is deeply rooted in public consciousness. Since ancient times, Bao Gong has been highly admired. The Bao Gong Temple, built before the Ming Dynasty, was primarily constructed to commemorate Bao Gong. During the Qing Dynasty, Li Hongzhang invested heavily in its renovation.

Text 3: I visited the Humble Administrator's Garden in the afternoon and spent two hours exploring. The scenery is remarkable; it is, after all, one of the four famous gardens in China. I particularly enjoyed its "borrowed scenery" technique. The park features a variety of buildings that harmoniously complement the landscape, making it highly recommended. Renting an interpreter is an option; however, note that the duration should not exceed one hour to avoid high costs.

Text 4: The scenic spot is conveniently located near the city, just a short drive away. I bought a package ticket for 110 yuan, which was cost-effective. The route offers views of mountains and rivers, and some sites have very vivid names. The spot also features glass rafting and a sightseeing elevator. Visitors can enjoy continuous performances during the boat ride, adding interest to the experience.

(3) Relationship matrix of landscape culture perception

Tagging the introduction texts of scenic spots on tourism websites, coding scenic spots, categorizing the cultural perception of scenic spots, and constructing the relationship matrix between landscape resources and cultural perception types were conducted according to the theoretical logic. Finally, 222 landscape resource tags were summarized, with some relationship matrices shown in Table no. 2, where 1 indicates “related” and 0 indicates “unrelated.”

**Table no. 2. The relationship matrix of cultural perception of tourism landscape**

Tourism Landscape	Location code (top four)	Landscape resources	Cultural perception of landscape resources			
			Modern humanity	Ancient nature	Modern nature	Ancient humanity
Jiuhua Mountain in Chizhou, Anhui Province	2428	“natural scenery”	0	1	1	0
		“cultural relics”	0	0	0	1
Shanghai Oriental Pearl	2001	“high-altitude landscape”	1	0	1	0
.....	.....	.....	.....	.....	.....	.....
Changzhou Dinosaur Valley Hot Spring, Jiangsu	2131	“soaking in hot springs”	0	1	1	0
Huayi Brothers Film World	2151	“amusement park”	1	0	0	0

**2.3. The influence mechanism**

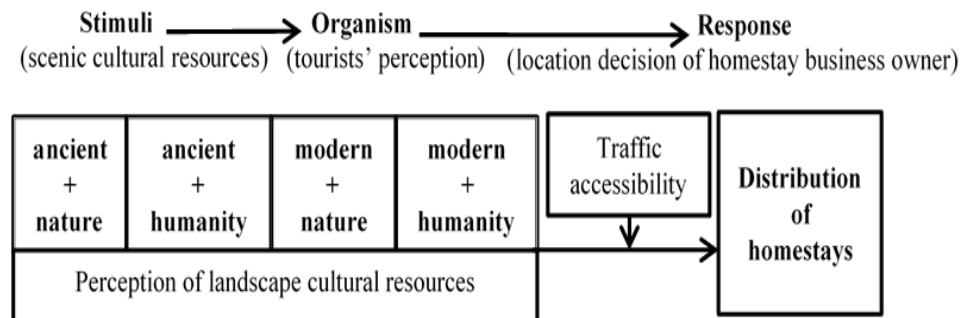
To explore how tourists' perceptions of landscape culture influence the distribution of homestay businesses more deeply, this research adopts the S-O-R model (Stimulus-Organism-Response Model), dividing the process that influences consumer decision-making into three main stages:

**Stage 1: Perception and Information Acquisition.** Tourists use online platforms such as Ctrip and Qunar to comprehensively understand the cultural resources of scenic spots and the attributes of homestay products. The abundant information provided by digital platforms helps tourists form perceptions of landscape cultural resources. This cultural perception is influenced not only by the characteristics of the landscape itself but also by the cognitive processes of the tourists. For example, although faux-ancient architecture is modern in construction, it can still evoke tourists' perception of ancient culture; conversely, the use of modern elements can give traditional landscapes a contemporary feel. This process highlights the importance of digital cultural dissemination, as tourists gradually build awareness and interest in destination cultural resources through browsing online information.



**Stage 2: Formation and Reinforcement of Motivation.** When the cultural resources of a scenic area obtained online align with the tourists' preferences, the stimuli provided by digital platforms further strengthen their motivation. Tourists' prior cognition and emotional interaction are reinforced, and digital cultural content gradually transforms into their motivation to visit the scenic spot. At the same time, tourists can complete online bookings for transportation and homestays via digital platforms, reducing the decision-making cycle. Personalized recommendations further enhance their willingness to travel (Xu and Luo, 2023).

**Stage 3: Experience and Feedback.** Tourists convert their perceptions into real consumption behaviors by physically experiencing the cultural resources of the scenic area and staying at homestays. At this stage, accessibility becomes a critical factor. Scenic spots and homestays with convenient transportation are better able to attract tourists, strengthening the impact of cultural resources on the clustering of homestays. After experiencing the landscape culture and homestay products, tourists often post feedback online, such as ratings or travel blogs. This online feedback not only reflects their consumption experience but also provides valuable information for other potential tourists, forming a new cycle of information dissemination (Bridges and Vásquez, 2018). The experience of tourists visiting attractions affects the site selection decisions of homestay business owners, which in turn influences the distribution of homestays, as illustrated in Figure no. 2.



**Figure no. 2. The influence mechanism of landscape culture perception on the distribution of homestay**

### 3. Association induction between landscape cultural perception and homestay spatial distribution

#### 3.1. Variables

**independent variables.** The independent variable is the perception of tourism landscape culture, weighted according to ratings by the Ministry of Culture and Tourism. If a scenic spot has a national rating of 5A, it scores 10 points; 4A scores 8 points, and 3A and below scores 2 points. The total score for each zip code area is calculated by multiplying the number of scenic spots at each grade by its weight, then summing these values. Equation (1) shows how to calculate the representation intensity of the four types of cultural resource perception across 154 zip codes.

$$x_{ij} = \sum (R_K * N_{ijk}) \quad (1)$$

In Formula (1),  $i$  represents the type of independent variable  $x$  ( $i=1,2,3,4$ );  $j$  is the corresponding postal code area number ( $j=1,2,3,\dots$ );  $K$  denotes the grade of the scenic area (5A, 4A, 3A, or below);  $R$  is the assigned value for the scenic area grade (10 for 5A, 8 for 4A, and 2 for 3A or below); and  $N$  is the number of scenic areas in the corresponding region.

**dependent variables.** The dependent variable is the spatial distribution of homestays, measured by location entropy, a concept introduced by P. Haggett and applied to location analysis. The formula for calculating location entropy is provided in Equation (2).

$$LQ_{ij} = \frac{q_{ij}/q_i}{q_i/q} \quad (2)$$

In Formula (2),  $LQ_{ij}$  represents the location quotient of homestays  $i$  in region  $j$  within the Yangtze River Delta.  $q_{ij}$  is the number of homestays  $i$  in region  $j$ ,  $q_j$  is the total number of enterprises in region  $j$ ,  $q_i$  denotes the number of homestays  $i$  in the Yangtze River Delta, and  $q$  represents the total number of enterprises in the Yangtze River Delta.

**Moderating variable.** The moderating variable is traffic accessibility, which is also evaluated using scores from Ctrip online tourists. When selecting a homestay, the ease of access, convenience of staying, and the overall travel convenience are critical factors. Therefore, tourists' perceptions of traffic accessibility significantly influence their choice of accommodations. Homestays with good transportation links tend to have a competitive advantage, while those with poor access may be less favoured despite rich cultural resources. Thus, traffic accessibility affects the distribution of Homestays.

**Control variables.** The control variables include the characteristics of homestay products, such as price, cleanliness, landlord services, and decoration. These values are derived from the ratings given by online tourists on Ctrip.

The price of a homestay is determined by multiple factors, including its location, quality, and other aspects, and serves as a key criterion for tourists in selecting accommodations. The cleanliness of the premises is a basic requirement for tourists, particularly in the post-COVID-19 era, where hygiene and health standards have become more stringent. The landlord's service quality and the interior decoration of the homestay reflect both the host's efforts and the environment, directly or indirectly showcasing local customs and culture. Various levels of service and decoration can significantly impact the success or failure of a homestay's operation and its distribution characteristics.

### 3.2. Empirical model

**Benchmark Model.** The initial model examines the impact of four types of landscape cultural perceptions on the distribution of Homestays, as shown in Equation (3).

$$Y_i = \alpha_0 + \alpha_n X_n + \gamma \text{Contr} + \varepsilon_i \quad (3)$$

In formula (3),  $Y_i$  represents homestay gathering degree,  $X_n$  represents four types of cultural perceptions ( $n = 1, 2, 3, 4$ ), where  $X_1$  represents ancient humanities,  $X_2$  represents ancient nature,  $X_3$  represents modern humanities, and  $X_4$  represents modern nature.  $\alpha_0$  is the

constant term, and  $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \gamma$  are the coefficients to be estimated. *Contr* represents a series of control variables, including homestay price, hygiene, service, and decoration.  $\varepsilon_i$  represents the random error term.

**Regulatory effect model.** Based on the benchmark model (3), the cross terms of explanatory variables and control variables are added, and the formula (4) is obtained, which is used to verify the moderating effect of traffic accessibility on the influence of four kinds of cultural perceptions on the hotel agglomeration.

$$Y_i = \beta_0 + \beta_n X_n + \beta_{n+1} X_n Tra + \gamma Contr + \varepsilon_i \quad (4)$$

In Formula (4),  $Y_i$  represents homestay gathering degree,  $\beta_0$  is the constant term, and  $\beta_1, \beta_2, \gamma$  are the constants to be estimated.  $X_n$  represents the four types of cultural perception ( $n=1, 2, 3, 4$ ), and *Tra* stands for traffic accessibility.

### 3.3. Data

The primary data on homestays and landscapes are mainly sourced from Ctrip.com (<https://www.ctrip.com>), covering cross-sectional data of 18,025 homestays and 5,659 scenic spots in 27 cities of the Yangtze River Delta. The enterprise data within each postal code area are obtained from the Yellow Pages website, Shunqi.com (<https://www.11467.com>).

In the empirical analysis, based on the first four digits of the postal codes, the spatial scope of these 27 cities is divided into 154 sub-sample areas. As shown in Table no. 3, it presents the detailed information of the variables, their meanings, and the descriptive statistics of the basic data.

**Table no. 3. Symbols, meanings and descriptive statistics of variables**

Variable	Name	Meaning	observed value	Average value	Standard deviation	mini	maxi
Dependent variable	Homestay gathering degree	Location Entropy of homestay Enterprises	5659	1.08	1.66	0	7.67
Independent variables	Cultural resources	Ancient Humanities (x1)	5659	26.22	58.37	0	406
		Ancient Nature (x2)	5659	12.64	19.43	0	128
		Modern Humanities (x3)	5659	42.49	101.85	0	736
		Modern Nature (x4)	5659	9.74	15.08	0	100
Moderating variable	Traffic accessibility	The convenience of transportation for consumers.	18025	3.36	1.35	0	5
Control variables	Price	Select the price of the basic standard room of the homestay.	18025	460.5	283.41	69.0	1481
	Clean	Is the room sanitary satisfactory to customers?	18025	3.46	0.95	0.19	5
	Service and decoration	The service quality of the campers, the quality of the	18025	3.23	1.48	0	5

Variable	Name	Meaning	observed value	Average value	Standard deviation	mini	maxi
		internal hardware facilities and the interior decoration of the homestay.					

### 3.4. Association induction

#### (1) Benchmark regression and collinearity diagnosis

Due to the large numerical differences among the variables, all variables were standardized, and ordinary least squares (OLS) regression was applied to examine the influence of landscape cultural perception on the distribution of homestay enterprises. Linear regression was conducted using the OLS method to determine whether different types of landscape cultural perceptions affect the location entropy of Homestays, as shown in Table no. 4. The table illustrates the relationship between different types of cultural perception and the distribution of homestay enterprises. Models 1, 2, 3, and 4 demonstrate that ancient humanities, ancient nature, modern humanities, and modern nature significantly impact the location entropy of homestays. Model 5 shows the combined effect of all four cultural perceptions on location entropy, with X2 and X3 being significant while X1 and X4 are not. The VIF values for X1 and X3 exceed 10, indicating multicollinearity. Therefore, ridge regression analysis is used to address the multicollinearity issue.

Table no. 4. Results of linear regression analysis

	Model 1	Model 2	Model 3	Model 4	Model 5	VIF
constant	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-
X1	0.372*** (4.902)				-0.219 (-0.934)	11.028
X2		0.309*** (4.089)			0.176** (2.042)	1.488
X3			0.407*** (5.415)		0.506** (2.093)	11.691
X4				0.314*** (3.997)	0.037 (0.358)	2.086
Price	0.154** (2.084)	0.103 (1.345)	0.162** (2.214)	0.126* (1.665)	0.135* (1.824)	1.090
Clean	0.013 (0.134)	0.087 (0.886)	0.012 (0.123)	0.039 (0.404)	0.048 (0.507)	1.801
Ser&Dec	0.127 (1.309)	0.161 (1.637)	0.109 (1.136)	0.120 (1.200)	0.090 (0.935)	1.850
N	154	154	154	154	154	-
Adj. R <sup>2</sup>	0.201	0.165	0.224	0.162	0.234	-

Source: compiled by authors. Note: \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

#### (2) Ridge Regression

The relationship between tourists' perceptions of landscape resources and culture is categorized into four types. To address multicollinearity without excluding any variables, ridge regression analysis is employed. Ridge regression is an improved version of the OLS method where the matrix  $XTX$  in OLS regression is replaced by  $(XTX + kI)$ , resulting in a

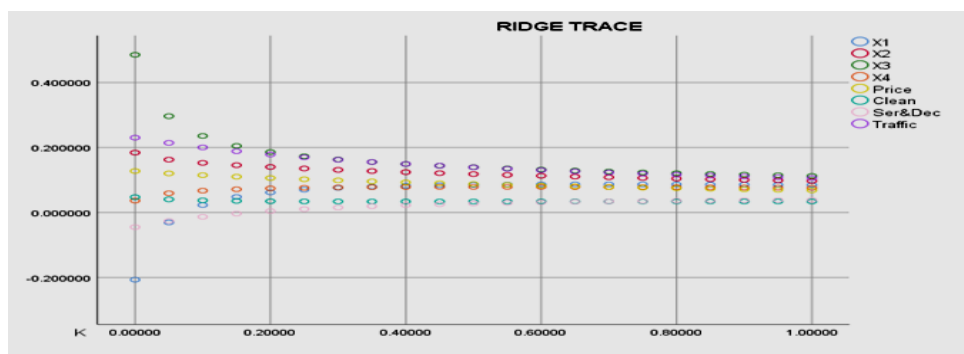
biased estimate of  $\beta$ , where  $K$  is the ridge parameter. By selecting an appropriate value for  $K$ , the mean square error is minimized, yielding better results than OLS regression. The ridge regression analysis outputs the ridge parameter  $K$ , coefficient estimates, and a ridge trace plot, as illustrated in Table no. 5 and Figure no. 3. The ridge regression coefficients stabilize when  $k=0.5$ , thus this value is selected.

Based on the ridge regression analysis, eight variables are processed, and the standard regression coefficients are obtained using the ridge trace plot to select the appropriate  $K$  value. The results are presented in Table no. 5.

**Table no. 5. Ridge regression coefficient**

K	R2	X1	X2	X3	X4	Price	Clean	Ser&Dec
0	0.26905	-0.21945	0.17624	0.506486	0.03658	0.134736	0.04817	0.089961
0.05	0.26554	-0.03462	0.155522	0.308454	0.061575	0.126835	0.047171	0.089118
0.1	0.26277	0.021485	0.146443	0.244675	0.07065	0.121028	0.047568	0.087115
0.15	0.26089	0.047683	0.140284	0.212456	0.075533	0.116054	0.048012	0.085131
0.2	0.2594	0.062341	0.1354	0.192617	0.078546	0.111621	0.04834	0.083297
0.25	0.2581	0.071382	0.131243	0.178926	0.08051	0.107603	0.048541	0.081612
0.3	0.25689	0.077288	0.127568	0.168748	0.081805	0.103924	0.048631	0.080059
0.35	0.25571	0.081278	0.124248	0.160771	0.082643	0.100533	0.048629	0.078616
0.4	0.25456	0.084021	0.121204	0.154271	0.083151	0.09739	0.048553	0.077266
0.45	0.2534	0.085911	0.118387	0.148813	0.083414	0.094466	0.048416	0.075996
0.5	0.25223	0.087197	0.115759	0.144121	0.083489	0.091735	0.048231	0.074793
0.55	0.25105	0.088042	0.113294	0.140011	0.083419	0.089177	0.048007	0.073649
0.6	0.24985	0.088558	0.110972	0.136354	0.083234	0.086775	0.047751	0.072557
0.65	0.24864	0.088823	0.108776	0.13306	0.082959	0.084513	0.047469	0.071511
0.7	0.24742	0.088896	0.106693	0.13006	0.082611	0.082378	0.047167	0.070506
0.75	0.24619	0.088818	0.104712	0.127304	0.082204	0.08036	0.046849	0.069539
0.8	0.24494	0.088621	0.102823	0.124753	0.081751	0.078449	0.046518	0.068606
0.85	0.24369	0.08833	0.101019	0.122376	0.08126	0.076634	0.046176	0.067704
0.9	0.24242	0.087964	0.099292	0.12015	0.080739	0.07491	0.045826	0.066831
0.95	0.24115	0.087537	0.097637	0.118055	0.080194	0.073269	0.045471	0.065985
1	0.23987	0.087062	0.096047	0.116074	0.07963	0.071704	0.045111	0.065164

Source: compiled by authors.



**Figure no. 3. Ridge trace map**

As shown in table no. 6, the coefficients for ancient humanities, ancient nature, modern humanities, and modern nature are significantly positive, indicating that incorporating these four types of cultural perceptions can enhance the agglomeration of homestay businesses. The influence of these cultural types, in descending order, is modern humanity, ancient nature, ancient humanity, and modern nature. The findings align with reality, as modern cultural landscapes serve as excellent carriers of cultural brands, such as the Shanghai Oriental Pearl Tower and Disneyland, all recognized for their regional characteristics and high commercial value. Similarly, many well-known ancient natural landscapes in the Yangtze River Delta, such as West Lake Hangzhou and Gardens Suzhou, maintain their traditional cultural attributes while attracting tourists worldwide, thereby promoting local tourism and the homestay industry.

**Table no. 6. Ridge regression analysis results**

	Coefficient of regression	VIF value
constant	0.000 (0.000)	-
X1	0.087** (2.388)	0.260
X2	0.116** (2.416)	0.448
X3	0.144*** (4.047)	0.248
X4	0.083* (1.765)	0.437
Price	0.092* (1.923)	0.444
Clean	0.048 (1.036)	0.423
Ser&Dec	0.075 (1.601)	0.426
N	154	
Adj. R <sup>2</sup>	0.216	

Source: compiled by authors. Note: \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

### (3) Moderating Effect Test

Building upon the benchmark regression, this paper further examines the moderating effect of traffic accessibility on the distribution of Homestays with respect to landscape cultural perception. The moderating effect of traffic accessibility is tested separately. Models 6, 7, and 8 assess traffic accessibility's impact on the location entropy of Homestays in ancient contexts, while Models 9, 10, and 11 examine its effect on homestay location entropy for ancient times. Models 12, 13, and 14 test traffic accessibility in the context of modern humanities, while Models 15, 16, and 17 evaluate its effect on modern natural contexts. The moderating effect is analyzed using cross-products of diverse types of landscape cultural perceptions and traffic accessibility, with results shown in Table no. 7.

Table no. 7. Traffic accessibility moderating effect results

	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17
constant	0.000 (0.000)	-0.000 (-0.000)	-0.011 (-0.142)	0.000 (0.000)	0.000 (0.000)	-0.021 (-0.307)	0.000 (0.000)	-0.000 (-0.000)	-0.001 (-0.010)	0.000 (0.000)	-0.000 (-0.000)	-0.031 (-0.422)
X1	0.372*** (4.902)	0.369*** (4.951)	0.324** (2.600)									
X2				0.309*** (4.089)	0.314*** (4.243)	0.252*** (3.560)						
X3							0.407*** (5.415)	0.402*** (5.439)	0.398*** (2.765)			
X4										0.314*** (3.997)	0.311*** (4.031)	0.234*** (2.613)
Traffic		0.230** (2.587)	0.235*** (2.614)		0.247*** (2.723)	0.247*** (2.894)		0.224** (2.552)	0.224** (2.512)		0.232** (2.542)	0.242*** (2.663)
X1* Traffic			0.056 (0.453)									
X2* Traffic						0.372*** (4.548)						
X3* Traffic									0.004 (0.028)			
X4* Traffic												0.148* (1.684)
Price	0.154** (2.084)	0.149** (2.045)	0.154** (2.086)	0.103 (1.345)	0.096 (1.285)	0.188** (2.575)	0.162** (2.214)	0.156** (2.174)	0.156** (2.149)	0.126* (1.665)	0.121 (1.621)	0.141* (1.873)
Clean	0.013 (0.134)	0.010 (0.109)	0.013 (0.139)	0.087 (0.886)	0.085 (0.882)	0.122 (1.341)	0.012 (0.123)	0.009 (0.099)	0.009 (0.101)	0.039 (0.404)	0.037 (0.381)	0.032 (0.337)
Ser&Dec	0.127 (1.309)	-0.009 (-0.079)	0.001 (0.010)	0.161 (1.637)	0.013 (0.121)	0.057 (0.545)	0.109 (1.136)	-0.022 (-0.207)	-0.022 (-0.196)	0.120 (1.200)	-0.016 (-0.140)	0.023 (0.199)
N	154	154	154	154	154	154	154	154	154	154	154	154
Adj. R <sup>2</sup>	0.201	0.230	0.226	0.165	0.200	0.294	0.224	0.252	0.247	0.162	0.191	0.201

Source: compiled by authors. Note: \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

Traffic accessibility positively influences the impact of ancient and modern natural landscapes on the location entropy of Homestays. As traffic accessibility improves, the perceptions of natural and human landscapes become stronger, encouraging more homestays to cluster. However, traffic accessibility does not significantly influence location entropy concerning ancient and modern humanities. Compared to human-made landscapes, natural landscapes typically arise from the intrinsic state of nature and minimally affected by human activities (e.g., rivers, mountains, forests). Preserving such natural scenery often complicates developing tourist transportation infrastructure, such as steep mountain peaks accessible only by cable cars. Ideally, a homestay should be located near city centers with comprehensive facilities to meet diverse needs, enhancing travel and daily convenience. Hence, traffic accessibility in landscapes with natural and cultural perceptions has a positive moderating effect. An effective tourist transportation network is essential for enhancing the tourist experience, balancing the originality of natural scenery and accessibility, thereby facilitating easy and convenient access to natural landscapes.

(4) Robust test

To further validate the reliability of the conclusions, a robustness test was conducted by substituting the explanatory variables. Two main adjustments were made: first, using a ratio method to calculate the number of scenic spots in the corresponding area to minimize dimensional influence; and second, reducing the impact of scenic spot grades by adjusting the weights assigned to different scenic spot grades. The specific calculation method for the independent variables is shown in Equation (6).

$$x_{ij} = \overline{R}_{jk} * \left( \frac{N_{ij}}{\sum N_{ij}} \right) \quad (6)$$

In Formula (5),  $i$  denotes the type of independent variable  $x_{ij}$  ( $i=1,2,3,4$ );  $j$  is the corresponding postal code area number ( $j=1,2,3,\dots$ );  $K$  represents the grade of the scenic area (5A, 4A, 3A, or below);  $R$  is the assigned value for the scenic area grade (5 for 5A, 4 for 4A, and 2 for 3A or below); and  $N$  is the number of scenic areas in the corresponding region.

Even after modifying the calculation method for the independent variables, multicollinearity persisted, as shown in Table no. 8. Consequently, the ridge regression method was employed for robustness testing, with results presented in Table no. 9.

**Table no. 8. Robustness test of linear regression analysis**

	Model 18	Model 19	Model 20	Model 21	Model 22	VIF
constant	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (-0.000)	0.000 (0.000)	-
X1	0.327*** (4.289)				-0.342* (-1.752)	7.621
X2		0.351*** (4.687)			0.194* (1.675)	2.675
X3			0.399*** (5.326)		0.490** (1.995)	12.086
X4				0.411*** (5.390)	0.104 (0.518)	8.034
Price	0.148* (1.969)	0.103 (1.370)	0.157** (2.152)	0.132* (1.814)	0.130* (1.765)	1.093
Clean	0.043 (0.446)	0.105 (1.083)	0.027 (0.290)	0.033 (0.349)	0.055 (0.575)	1.839
Ser&Dec	0.131 (1.331)	0.131 (1.342)	0.108 (1.126)	0.083 (0.859)	0.091 (0.948)	1.856
N	154	154	154	154	154	-
Adj. R <sup>2</sup>	0.174	0.191	0.220	0.223	0.236	-

Source: compiled by authors. Note: \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\*  $p < 0.01$ .

From Table no. 9, the robustness test's regression coefficient results are consistent with previous findings. Ancient nature, modern humanities, and modern nature show significant positive influences, indicating that increasing these three types of cultural perceptions can promote the clustering of homestay businesses, while ancient humanities do not have a



significant effect on their distribution. The results of robustness test of regulation effect are shown in Table no. 10.

**Table no. 9. Ridge regression analysis robustness test (K=0.5)**

	Coefficient of regression	VIF value
constant	0.000 (0.000)	-
X1	0.024 (0.632)	0.287
X2	0.109** (2.347)	0.419
X3	0.127*** (3.666)	0.232
X4	0.130*** (3.449)	0.275
Price	0.092* (1.917)	0.444
Clean	0.055 (1.188)	0.420
Ser&Dec	0.076 (1.613)	0.425
N	154	
Adj. R <sup>2</sup>	0.211	

Source: compiled by authors. Note: \*p<0.10, \*\*p<0.05, \*\*\* p<0.01.

From Table no. 10, it is evident that traffic accessibility has a significant positive moderating effect on the clustering of homestays influenced by ancient humanities, ancient nature, and modern nature. It is good transportation links that win a competitive edge. However, the moderating effect on modern humanities is insignificant. This can be attributed to the fact that modern humanities landscapes are primarily located within urban networks, where they closely align with tourist traffic patterns and perceptions of accessibility. Consequently, traffic accessibility exerts a significant moderating effect on the relationship between perceptions of natural landscapes and the distribution of homestays. In contrast, its influence on the distribution associated with perceptions of human-culture landscapes is relatively marginal.

**Table no. 10. Robustness results of traffic accessibility moderating effect**

	Model 23	Model 24	Model 25	Model 26	Model 27	Model 28	Model 29	Model 30	Model 31	Model 32	Model 33	Model 34
constant	0.000 (0.000)	-0.000 (-0.000)	-0.026 (-0.368)	0.000 (0.000)	0.000 (0.000)	-0.024 (-0.356)	0.000 (0.000)	-0.000 (-0.000)	-0.025 (-0.346)	-0.000 (-0.000)	-0.000 (-0.000)	-0.035 (-0.525)
X1	0.327*** (4.289)	0.323*** (4.380)	0.197** (1.998)									
X2				0.351*** (4.687)	0.352*** (4.890)	0.242*** (3.218)						
X3							0.399*** (5.326)	0.392*** (5.417)	0.269** (2.302)			
X4										0.411*** (5.390)	0.418*** (5.714)	0.298*** (3.631)

	Model 23	Model 24	Model 25	Model 26	Model 27	Model 28	Model 29	Model 30	Model 31	Model 32	Model 33	Model 34
Traffic		0.283*** (3.382)	0.286*** (3.455)		0.291*** (3.538)	0.312*** (3.937)		0.277*** (3.408)	0.280*** (3.456)		0.300*** (3.738)	0.296*** (3.777)
X1* Traffic			0.173* (1.892)									
X2* Traffic						0.298*** (3.690)						
X3* Traffic									0.139 (1.336)			
X4* Traffic												0.216*** (2.939)
Price	0.148* (1.969)	0.144* (1.974)	0.163** (2.238)	0.103 (1.370)	0.098 (1.355)	0.157** (2.201)	0.157** (2.152)	0.153** (2.161)	0.165** (2.323)	0.132* (1.814)	0.128* (1.821)	0.168** (2.415)
Clean	0.043 (0.446)	0.047 (0.500)	0.063 (0.671)	0.105 (1.083)	0.109 (1.168)	0.121 (1.343)	0.027 (0.290)	0.031 (0.342)	0.043 (0.476)	0.033 (0.349)	0.037 (0.405)	0.044 (0.505)
Ser&Dec	0.131 (1.331)	-0.018 (-0.167)	0.009 (0.082)	0.131 (1.342)	-0.025 (-0.238)	0.006 (0.060)	0.108 (1.126)	-0.037 (-0.360)	-0.012 (-0.114)	0.083 (0.859)	-0.079 (-0.768)	-0.027 (-0.264)
N	154	154	154	154	154	154	154	154	154	154	154	154
Adj. R <sup>2</sup>	0.174	0.228	0.241	0.191	0.249	0.308	0.220	0.272	0.276	0.223	0.285	0.320

Source: compiled by authors. Note: \*p<0.10, \*\*p<0.05, \*\*\* p<0.01.

#### 4. Conclusion

This research, through theoretical deduction and empirical analysis, delves into the impact of landscape cultural perception on the spatial distribution of homestay businesses, and arrives at the following conclusions:

Firstly, considering landscape cultural perception as an endogenous variable within the homestay distribution model, it manifests a remarkable influence on tourist behavior. The tourist decision - making process can be segmented into three phases. Initially, tourists amass information regarding cultural landscape resources and homestay attributes via media platforms, thereby forming cultural perceptions. Once this information converges with their preferences, it kindles their consumption motivation. Finally, through cognitive and emotional interactions, tourists determine to visit the destination and select a homestay. In this process, transportation accessibility emerges as a pivotal factor. Homestays with superior transportation conditions are more likely to attract tourists, and landscape cultural perception also exerts a significant impact on the spatial distribution of homestays.

Secondly, the research categorizes cultural perceptions into four types: ancient humanities, modern humanities, ancient nature, and modern nature. A perception matrix is constructed to probe into the theoretical correlation between landscape resources and cultural perceptions. These four types of cultural perceptions exert varying degrees of influence on the spatial distribution of homestay businesses in the Yangtze River Delta region. The perception of modern humanities has the most pronounced effect on homestay clustering, followed by ancient nature and ancient humanities, while modern nature has the weakest impact. Around modern humanistic landscapes such as the Oriental Pearl Tower, Disneyland, and science museums in Shanghai, homestay businesses are highly concentrated, attracting a large number of tourists, thus demonstrating substantial

commercial value. The moderating effect of transportation accessibility is particularly conspicuous in the relationship between natural landscape perceptions and homestay distribution. Improved transportation conditions enhance tourists' capacity to access natural landscapes, thereby augmenting their perception of these landscapes and further propelling the clustering of homestay businesses. Conversely, transportation accessibility has a relatively weaker moderating effect on the relationship between humanistic landscape perceptions and homestay distribution, as humanistic landscapes are typically situated in urban or densely-populated areas with already convenient transportation. Consequently, further improvements in transportation conditions have a limited impact on the distribution of homestays in these regions.

Finally, the research accentuates the indispensable role of digital technology in the cultural tourism industry. Digital platforms, by integrating multifaceted information such as the historical background, cultural features, and tourist reviews of scenic spots, offer tourists comprehensive cultural resource guides. The pre-acquisition of this information not only facilitates tourists in better trip planning but also heightens their awareness and anticipations of the cultural aspects of the destinations, thereby enriching their overall travel experience. Simultaneously, online booking systems streamline the processes of accommodation, ticket, and activity arrangements, enabling tourists to make swifter decisions, reduce uncertainties during the trip, and markedly improve travel efficiency and satisfaction. For homestay businesses, digital tools endow them with highly targeted marketing capabilities. For example, big data analysis enables insights into tourist behavior preferences, facilitating customized promotional strategies (Senyao & Ha, 2022). Additionally, digital platforms furnish homestay owners with efficient management tools, automating processes from real-time booking management to customer relationship maintenance, reducing labor costs, and enhancing operational efficiency. Moreover, the digital feedback mechanism empowers homestay businesses to promptly respond to tourist demands and reviews, continuously optimizing service quality. This data-driven management approach not only bolsters the competitiveness of homestay businesses but also fosters their long-term stable development in regional tourism markets. By integrating digital technology with differentiated strategies for landscape culture, this research provides robust support for the sustainable development of the cultural tourism industry (Pasanchay & Schott, 2021). On one hand, digital tools enable tourists to gain a deeper understanding of the cultural aspects of tourist destinations, promoting broader dissemination of cultural resources; on the other hand, homestay operators, through refined management and targeted marketing, further enhance the interactive effects between scenic spots and homestays, thereby augmenting the overall value of regional tourism.

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