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A STUDY ON THE RELATIONSHIP BETWEEN SMART TOURISM, DESTINATION COMPETITIVENESS, DESTINATION IMAGE AND BEHAVIORAL INTENTION

[1] Chien-Wen Lo, [2] Chia-Nung Li
[1] Associate Professor, Department of Leisure and Recreation Administration, Ming Chuan University, [2] Professor, Department of Natural Resources, Chinese Culture University,

Abstract— The government is now actively promoting various applications that are conducive to smart urban and rural living, hoping to improve the tourist experience and enhance the competitiveness of the industry through smart tourism. This study investigates the interaction between smart tourism, destination competitiveness, destination imagery, and behavioral intentions. Firstly, this study uses the Fuzzy Delphi Method (FDM) to construct indicators that combine smart tourism and destination competitiveness and further compares urban and rural areas based on the Recreation Opportunity Sequence (ROS). The results show that in the smart tourism category, urban visitors are most likely to agree with "smart accessibility," while rural visitors are most likely to agree with "smart package service." In terms of destination competitiveness, visitors from both urban and rural areas were most supportive of the 'support factor.' Furthermore, the Least Square Structural Equation (PLS-SEM) shows that only smart tourism has no influence or other relationship with destination imagery, whether a city or a rural area, while all others have an influence. Therefore, it can be seen that destination competitiveness is an essential component that mainly affects destination imagery and can further influence the behavioral intentions of tourists. However, smart tourism can be considered a component of destination competitiveness and can therefore be included as an element of destination competitiveness affecting destination imagery. The above findings can serve as a reference for the development of smart tourism in both urban and rural areas and the allocation and investment of resources to enhance the competitiveness of destinations.

Index Terms—smart tourism, destination competitiveness, fuzzy Delphi method, leisure opportunity sequences, least square structural equation

I. INTRODUCTION

A smart city is defined as a city that improves the quality of life of its citizens while making it more competitive (Boes et al., 2015). Gretzel et al. (2015) emphasize the relevance of the concepts of smart cities and smart tourism. In particular, Smart Tourism Destinations are one of the key directions in which smart cities can be implemented (Boes et al., 2014; McCartney et al., 2008). Smart tourism results from the shift from smart cities to destinations (Baggio & Cooper, 2010). Smart destinations can be considered as seeds of smart cities, which are essential infrastructures shared by smart cities and smart destinations. The construction of infrastructure inevitably increases competitiveness and improves the visitor experience (Khan et al., 2017; Boes et al., 2015; Baser, 2019). Improving Destination Competitiveness is widely recognized as an important condition for reaping the benefits of tourism and consequently improving the quality of life for residents (Chin & Hampton, 2020; Ivanov & Ivanova, 2016). Many destinations use the 'smart' concept to provide uniqueness and differentiation in product and service offerings, thus giving smart destinations a competitive edge over other destinations (Tavitiyaman et al., 2021; Cornejo Ortega & Malcolm, 2020).

Furthermore, the spatial distribution of amenities plays a vital role in shaping urban and rural spaces (Dissart & Marcouiller, 2012).Based on the Recreation Opportunity Spectrum (ROS), recreational activities, environments, and experiences can be divided into a primitive area, semi-primitive/non-motorized, semi-primitive/motorized, roaded natural, rural area, and urban area (USDA Forest Service, 1986; McCool et al., 2007).Among these, urban and rural destinations have different dimensions of focus and different levels of infrastructure and tourism development (Romão et al., 2018; Rasoolimanesh et al., 2017; Naldi et al. & Page, 2011; Wall & Mathieson, 2005; Go & Govers, 1999; Gilbert & Clark, 1997). In the case of rural areas, smart tourism has contributed to the development of rural tourism (Zhu & Shang, 2021), and rural travelers value technological innovations in rural destinations, especially ICT facilities that add value to the tourism experience (Ballina, 2020); In the case of cities, urban infrastructure is relatively well developed, while the attractiveness and accessibility of attractions seem to be most important for tourists (Romão et al., 2018). Therefore, there are bound to be differences between urban and rural areas regarding what needs to be considered for smart tourism. Moreover, in addition to the factors that need to be considered for urban and rural destinations, the primary consideration is the impact of destination competitiveness and development on the development of smart tourism (Rasoolimanesh et al., 2017; Nicholas et al., 2009; Su & Wall, 2014; YANG, HSING-CHU and WANG, CHUN, 2006). However, is there a system of indicators that can be followed in the construction and design of smart tourism and destination competitiveness? What is the relationship between smart tourism and destination competitiveness? Do smart tourism and destination competitiveness affect destination imagery and behavioral intent? Is there a difference between urban and rural conditions? All of the above are important issues for discussion. Therefore, this study firstly constructs indicators of smart tourism and destination competitiveness and uses Partial Least Squares SEM (PLS-SEM) to understand the relationship between smart tourism and destination competitiveness and whether smart tourism and destination competitiveness affect destination imagery and behavioral intentions. With this in mind, the objectives of this study are summarized below:

1. Through the fuzzy Delphi method, we can construct a preliminary measure of smart tourism and destination competitiveness, which will be used as the basis for subsequent research.
2. Based on the Recreation Opportunity Series (ROS), urban areas can be differentiated from rural areas and further compared. This study uses questionnaires and least square structural equations to understand the relationship between urban and rural smart tourism and destination competitiveness and whether smart tourism and destination competitiveness affect destination imagery and behavioral intentions.

3. The findings of this study can serve as a reference for the allocation of resources and investment in the development of smart tourism and destination competitiveness in urban and rural areas.

Literature Review

1.1 Smart Tourism Destinations

Smart tourism is one of the key directions for the implementation of smart cities (Boes et. al., 2016; McCartney et. al., 2008). The trend of smart tourism is to provide travelers with a healthy, safe, and comfortable travel experience. Smart tourism destinations are an integral part of this, and smart tourist attractions within smart tourism destinations are gaining attention (HSU, FEI-FEI, and HUANG, LEI, 2018). The six classifications of destinations include attractions, accessibility, amenities, packages, activities, and ancillary services. There is also a large body of literature on the classification of smart tourism based on this 6A category (Baser et al., 2019; Lalicic & Önder, 2108; Boes et al., 2016; Boes et al, 2015; Wang et al., Buhalis & Amaranggana, 2013; Cohen, 2012; Zhang et al.). Furthermore, Buhalis & Amaranggana (2014) state that smart tourism is based on the concept of a smart city, which incorporates competitiveness, sustainability, and inclusiveness. Like smart cities, smart tourism can enhance their competitiveness (Ritchie & Crouch, 2005), and with the implementation of technology, smart tourism can enhance the tourist experience (Neuhofer et al., 2012). Later, Wang et al. (2016) classify smart tourist attractions into eight categories: smart-information systems, intelligent-tourism management, smart sightseeing, e-commerce system, smart safety, intelligent traffic, smart forecast, and virtual tourist attraction. Subsequently, Tavitiyaman et al. (2021) also explored smart tourism areas under several categories based on Wang et al.: smart information systems, intelligent-tourism management, smart sightseeing, e-commerce system, intelligent traffic, and smart forecast.

To summarize, although Buhalis (2000) has categorized tourism destinations into 6A, and there are many papers based on this as a basis for research on the relevance of tourism destinations to smart tourism, further definitions and classifications should be made by adding the element of intelligence to 6A. Therefore, this study combines the connotations of smart tourist attractiveness as proposed by Wang et al. (2016) and Tavitiyaman et al. (2021) and summarizes the following smart tourism categories (Figure 1): (I) Smart Attractions: including Smart natural attractions sightseeing, Smart artificial attractions sightseeing, Smart heritage attractions sightseeing, and Smart attraction management; (ii) Smart Accessibility: including Smart physical mobility, Smart digital mobility, Smart intelligent traffic, and E-tour map; (III) Smart Amenities: Smart built amenities, Smart environment monitoring, Smart information system, Smart tourism management, and Smart forecast. (IV) Smart Packages, including Smart type of accommodation, Smart services included, Smart co-creation package, and E-commerce system. (V) Smart Ancillary services, including Smart ancillary management, Virtual travel community, Smart stakeholder, Smart tourism organizations, and Smart safety; (VI) Smart Activities, including Smart business activities, Smart Leisure, and Smart virtual tourist attraction. This study summarizes the relevant literature to classify and organize smart tourism, as shown in Figure 1 below.

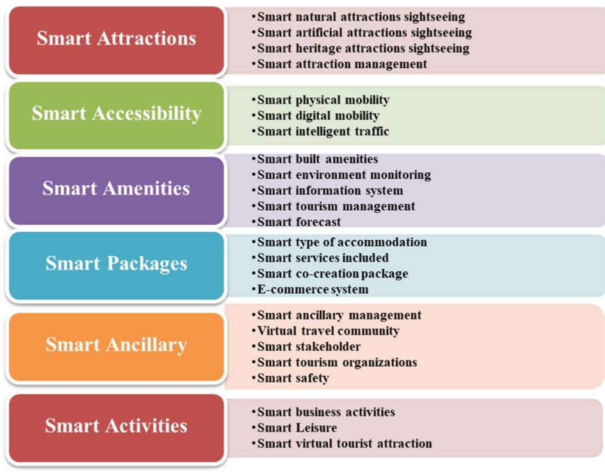

Figure 1. Smart Tourism Assessment Indicators.

1.2 Destination Competitiveness

The spatial distribution of amenities is an important determinant of tourism development, as it plays an important role in shaping urban and rural spaces (Dissart & Marcouiller, 2012).

However, urban and rural destinations do not focus on the exact dimensions and therefore have different levels of infrastructure and tourism development (Rasoolimanesh et al., 2017; Ashworth & Page, 2011; Gilbert & Clark, 1997; Wall & Mathieson, 2005). Generally speaking, 'village' is the opposite of 'urban.' According to Dernoi (1991), rural tourism excludes tourism activities outside the city. Most research has focused on rural areas and attractions near villages (Gursoy et al., 2002; McGehee & Anderek, 2004; Sharpley, 2014). Lack of tourist awareness of rural tourism, inadequate local planning, poor infrastructure, lack of operational talent and management, fewer sources of funding, and policy and institutional gaps are all inevitable (Naldi et al., 2015). In urban areas, urban infrastructure is relatively well-developed, and the attractiveness and accessibility of attractions seem to be most important for tourists (Romão et al., 2018). The multifunctional destination infrastructure of an urban area is a very important reason for tourists to be attracted to an urban area.

As a result, the number of urban facilities and services used by tourists is often high (Ashworth & Page, 2011; Edwards et al., 2008), such as leisure venues, accommodation, and dining venues, shows, festivals and events, city centers, cultural shows, etc. for tourists (Ashworth & Page, 2011).

As a result, there are inevitably differences between urban and rural areas in terms of what needs to be considered for smart tourism. Whether a destination attracts tourists or has advantages such as boosting the local economy needs to be considered in terms of local fundamentals and the competitiveness of the destination (Kulcsar, 2009). In general, while providing public facilities and infrastructure (e.g., roads, hotels, and recreational facilities) can increase tourist arrivals and satisfy the private sector's desire to maximize its economic benefits, this can endanger the urban and rural environment itself (Su & Wall, 2014). Therefore, a balance must be struck between the positive economic and social impacts of destination development and the need to protect the environment (Nicholas et al., 2009; Su & Wall, 2014).

By reference to the Travel & Tourism Competitiveness Report 2019, the Conceptual Model of Destination Competitiveness (CM) and the Integrated Model of Destination Competition (IM), and based on the five major theories of destination competitiveness proposed by Crouch and Ritchie (1999) and Ritchie & Crouch (2003), this study consolidates the competitiveness of smart urban and rural destinations and its assessment indicators, with five major components and other secondary components as follows: (a) 'Core Resources and Attractions': including, cultural resources, the hospitality of the local people, natural resources, and architectural styles; (b) "Tourism infrastructure": including accommodation, food and beverage, amusement facilities, and public transportation; (c) "Supporting Factors and Resources": including health and hygiene, tourism education of people, and ICT Readiness; (d) "Destination Management": environmental conservation, travel carrying capacity, management organization, travel organization; (e) Situational conditions: clean environment and fresh air, quiet areas, safe environment, natural disaster (Figure 5) (World Economic Forum, 2019; Zeng, Xibeng, 2012; RRomão et al., 2018; Naldi et al., 2015; Dissart & Marcouiller, 2012; Dwyer & Kim, 2003; Goeldner & Ritchie,2012; Go & Govers, 1999), as shown in Figure 2.

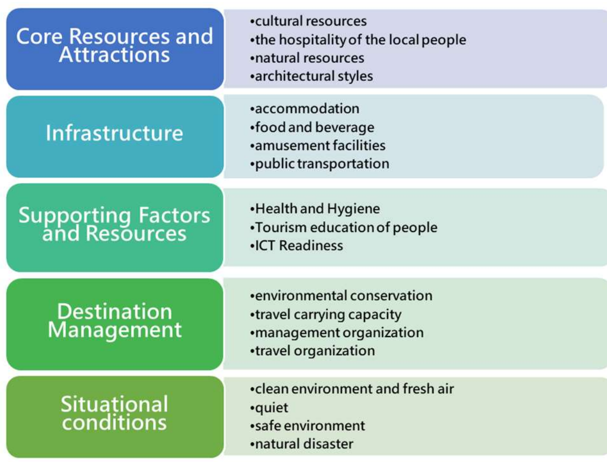

Figure 2 Destination Competitiveness Indicators

1.3 Destination Image

Destination image plays an important role in understanding travelers' behavioral intentions and decisions (Afshardoost & Eshaghi, 2020; Karl et al., 2020), meaning all the emotional perceptions an individual has of a place. These perceptions include experiences, beliefs, ideas, recollections, and impressions (Crompton, 1979; Echtner & Ritchie, 1991) but also involve an overall image composed of affective and cognitive imagery (Baloglu & McCleary, 1999). Cognitive imagery refers to an individual's beliefs and knowledge about a destination, which can be functional/tangible (e.g., landscape and cultural attractions) or psychological/abstract (e.g., feelings of hospitality and ambiance) (Martin & Bosque, 2008). Emotional imagery refers to the emotions or feelings that an individual may have about a destination. For example, the affective component relates to the emotions a destination can evoke (e.g., pleasure, excitement) (Martin & Bosque, 2008; Tan & Wu, 2016).

1.4 Behavioral Intention

In Ajzen's (1985) Theory of Planned Behavior (TPB), it is argued that human behavior is not entirely controlled by the will but is, in most cases, influenced by other external and objective environmental factors. Therefore, in order to increase the predictive and explanatory power of rational behavior theories for specific human behaviors, perceived behavioral control should be added in addition to attitudes and subjective norms in order to extend and modify the rational behavior theoretical framework. Ajzen's (1986) research more specifically suggests that an individual's behavior depends on the influence of his or her behavioral intentions. Attitudes, subjective norms, and perceived behavioral control are the three factors that influence behavioral intentions and affect behavior. Whereas attitude refers to an individual's feelings or positive and negative evaluations about engaging in a particular behavior , which may reflect the individual's feelings or perceptions of what the individual likes or dislikes about something; perceptions of behavioral control are perceptions of the degree of difficulty an individual feels when engaging in a particular behavior (Ajzen, 1991). Subjective norms refer to whether an individual perceives social pressure when engaging in a particular behavior. The pressure may originate from specific people or groups around the individual (Ajzen, 1991), such as friends, parents, siblings, and other family members.

Research Analysis

The study used expert questionnaires and the fuzzy Delphi method to construct the evaluation indicators. Based on the above-constructed indicators, a partial least square structural equation and an independent sample t-test were used to determine the relationship between smart tourism and destination competitiveness and urban-rural differences. The analysis and results of the study are discussed in the following sections.

3.1 Indicator Screening

3.1.1 Indicator Framework

In the assessment of smart tourism and destination competitiveness indicators, there are multiple influencing factors to be considered. In this study, a multiple criteria decision-making (MCDM) approach was adopted to analyze the criteria and to obtain the importance attached to them by experts through the fuzzy Delphi method in order to determine the applicability of the criteria and to select the criteria factors. The analysis results will serve as a reference and application basis for future smart tourism and destination competitiveness planning. The relevant research framework is shown in Figure 3.

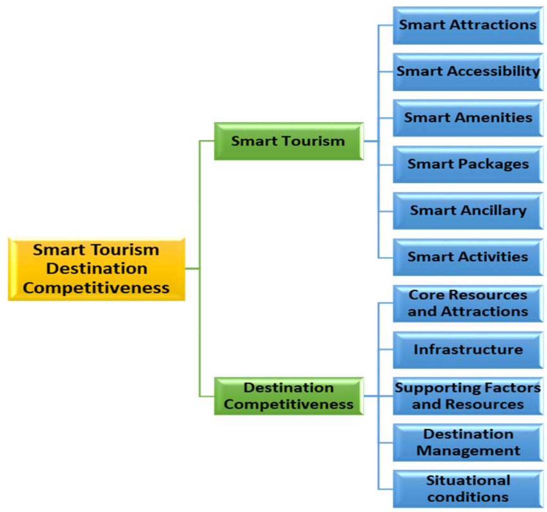

Figure 3. Smart Tourism and Destination Competitiveness Assessment Indicator Framework

3.1.2 Fuzzy Delphi Method (FDM)

The Fuzzy Delphi Method (FDM) is a factor screening method proposed by Murray et al. (1985), which combines the Delphi method with fuzzy theory to correct the shortcomings of the traditional Delphi method. It has the following advantages over the traditional Delphi method: 1. The fuzzy Delphi method can reduce the number of surveys. 2. The opinions of experts can be expressed more completely. 3. Expert knowledge can be made more rational and relevant through fuzzy theory. 4. It is more cost-effective in terms of time and cost. Furthermore, Ishikawa et al. (1993) applied fuzzy theory to the Delphi method and improved it, where the concept of cumulative number assignment and fuzzy points was used to integrate expert opinions into a fuzzy number, known as the fuzzy Delphi method.

3.1.3 Analysis of research findings

A total of 12 expert questionnaires were sent out for this study. Four professors in the field of tourism planning in academia, four directors of planning and design-related industries in the industry, and four government officials in the public sector related to tourism and planning were surveyed. The expert questionnaires were all valid. The completion of the expert questionnaires in the first stage of the study was based on the subjective assessment of the experts' professionalism, and the purpose of the questionnaires was to assess the order of importance in the evaluation form, using a scale of 0 to 10. The higher the rating, the more important it is. In this study, expert opinions were also aggregated and integrated according to the double triangular fuzzy number and a grey area check method proposed by CHENG and TSANG-PIN (2001). The results of the screening are shown in Table 1 below.

Table 1: Fuzzy Delphi Screening Results for Smart Tourism Competitiveness Assessment Indicators

		Minimum value		Maximum value		Geometric mean				
		Minimum	Maximum	Minimum	Maximu	Minimum	Optimum	Maximum	Z test	Consensus

		value	value	value	m value	value	value	value		value GI
Smart Tourism Destination	Smart Attractions Appeal	4	8	9	10	6.00	7.47	8.94	3.94	9.03
	Smart Accessibility	4	8	10	10	5.99	7.96	10	6.01	10.00
	Smart Amenities	3	8	7	9	4.58	6.53	8.49	2.90	7.30
	Smart Package Service	4	8	9	10	5.25	7.36	9.59	5.34	8.82
	Smart Assistive Services	4	7	8	9	5.66	6.80	7.94	3.28	8.05
	Smart Activities	1	8	5	9	2.63	4.69	6.61	2.19	5.69
Destination Competitiveness	Core resources and attractiveness	5	8	9	10	6.71	7.83	8.94	3.24	9.05
	Sightseeing facilities	4	8	8	10	5.66	7.30	8.94	3.29	8.00
	Supporting Elements	3	8	7	10	5.14	6.88	8.93	2.79	7.40
	Site Management	3	7	7	10	4.58	6.47	8.37	3.78	7.00
	Situational conditions	4	8	9	10	5.99	7.95	9.79	4.8	8.72

Note: The grey part is the assessment factor selected by the threshold value (6.00).

The results showed that a total of five indicators of smart tourism passed the threshold, and a total of five sub-indicators of destination competitiveness passed the threshold. Among the smart tourism indicators, there are five sub-indicators, including smart attractiveness of attractions, smart accessibility, smart amenities, smart package service, and smart activities;

Among the destination competitiveness indicators, there are five sub-indicators, including core resources and attractiveness, tourism services and facilities, supporting elements, destination management, and situational conditions. Among them, "smart accessibility", "core resources and attractiveness," and "smart attractiveness of attractions" are the top indicators according to experts' views.

3.2 Research Assumptions

After confirming the above indicators, this study distinguishes urban areas from rural areas based on the Recreational Opportunity Sequence (ROS) and makes further comparisons.

Although previous studies have shown that smart tourism has a competitive advantage over other tourism destinations (Tavitiyaman et al., 2021; Cornejo Ortega & Malcolm, 2020), urban and rural destinations have different dimensions of focus and therefore, different levels of infrastructure and tourism development (Romão et al., 2018; Rasoolimanesh et al., 2017; Naldi et al., 2015; Dissart & Marcouiller, 2012; Ashworth & Page, 2011; Wall & Mathieson, 2005; Go & Govers, 1999; Gilbert & Clark, 1997). However, in order to further synthesize the relationship between smart tourism and destination competitiveness and whether smart tourism and destination competitiveness affect destination imagery and behavioral intent, and to explore whether there are differences between urban and rural areas, this study proposes the following hypotheses:

Smart tourism is the seed of a smart city. Essentially, smart cities and smart tourism share an infrastructure. However, for tourists, the infrastructure must be built to take into account factors such as multilingualism, cultural differences, and seasonality of the visitor population, thus inevitably increasing competitiveness and improving the visitor experience (Khan et al., 2017; Boes et al., 2015). Smart information systems for destinations have become a very important strategy in enhancing the competitiveness of destinations (Luna-Nevarez & Hyman, 2012);

However, there is still a lack of understanding of the differences between urban and rural smart tourism and destination competitiveness. Therefore, we propose hypothesis 1:

Hypothesis 1: Urban/rural smart tourism has an impact on destination competitiveness

Smart tourism affects tourists' perceived imagery of the city (Chan, Peters, & Pikkemaat, 2019). Once an unforgettable smart tourism experience is formalized, tourists' overall image of the destination is enhanced (Sharma & Nayak, 2019). Kim et al. (2017) found that the quality of travel information in social media has an impact on destination imagery and is a key factor in influencing cognitive and emotional destination imagery.

However, it is also worth exploring whether different smart tourism characteristics between urban and rural areas have different impact effects, and therefore hypothesis 2 is proposed:

Hypothesis 2: Urban/village smart tourism has an impact on destination imagery

In destination competitiveness, core resources and attractions form the main elements of destination attractiveness and influence the shaping of destination imagery (Enright & Newton, 2005). Core resources and attractions are key features of destination competitiveness and help to enhance destination imagery (Vinyals-Mirabent, 2019). Once an unforgettable smart travel experience is developed, tourists enhance the overall image of the destination (Sharma & Nayak, 2019). However, it is worth exploring in depth whether different destination competitiveness characteristics in urban and rural areas have different effects on destination imagery, and therefore hypothesis 3 is proposed:

Hypothesis 3: Urban/rural destination competitiveness has an impact on destination imagery.

Destination imagery has a significant effect on behavioral intention, and behavioral intention becomes more positive as perceived destination imagery is enhanced (Liu et al., 2015). Cognitive and affective destination imagery significantly influences behavioral intention (Kaur et al., 2016; Tan and Wu, 2016; Souiden et al., 2017; Jalilvand and Heidari, 2017). Of these, holistic and affective imagery has the greatest influence on behavioral imagery, followed by cognitive imagery (Afshardoost & Eshaghi, 2020). However, it is worth exploring in depth whether different destination imagery and behavioral imagery have different impact effects between urban and rural areas, and therefore hypothesis 4 is proposed:

Hypothesis 4: Urban/rural destination imagery has an impact on behavioral intentions.

The composition of the population varies considerably according to the economic and social standards of the region in which the destination is located and the degree of tourism development.

The composition of residents in urban and rural destinations differs considerably, with the composition of residents in urban destinations being more diverse and those in rural destinations more homogeneous. Residents of urban destinations are more satisfied with the current state of tourism development than those of rural destinations. The difference in perceived destination imagery between urban and rural areas differs in terms of economic, environmental, and socio-cultural aspects (Yang Xingzhu and Wang Qun, 2006); However, in addition to the fact that different destination competitiveness between urban and rural areas will have different effects on destination imagery, the differences in smart tourism, destination imagery, and behavioral intention between urban and rural areas should be further explored, and therefore, Hypothesis 5 is proposed:

Hypothesis 5: The interplay of smart tourism, destination competitiveness, destination imagery and behavioral intent varies between urban and rural areas

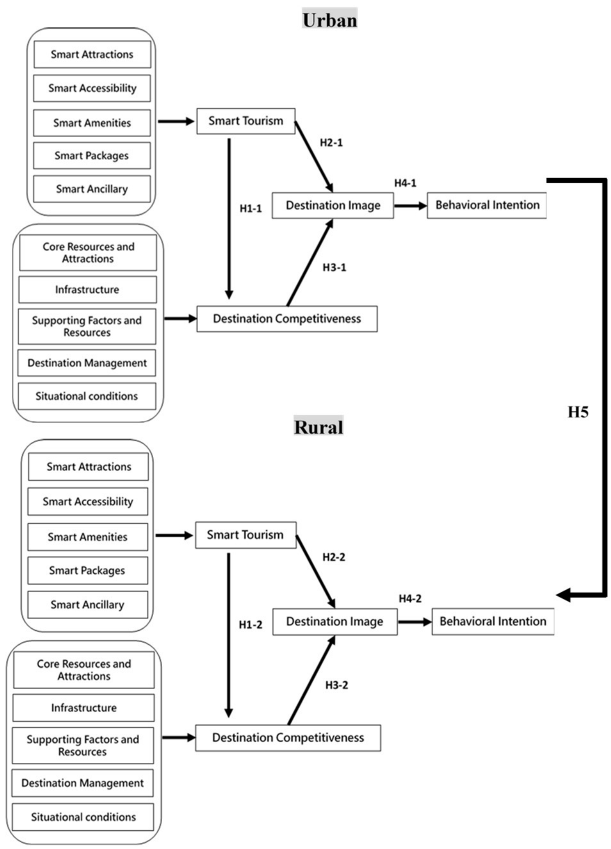

Fig. 3. Research Framework

Results

4.1 Smart tourism and destination competitiveness between urban and rural areas

This study further compares urban areas with rural areas based on the Recreation Opportunity Series (ROS). In this study, Taipei City was selected as the urban area, and Yilan County was selected as the rural area for the survey. According to the 2021 ROS survey conducted by the Ministry of Transportation and Communications (2022), Taipei City had 22,873,159 visitors to its ROS. Some of the more representative recreation sites are the Songshan Cultural and Creative Park, Huashan 1914 Creative Park, Taipei Zoo, and National Dr. Sun Yat-sen Memorial Hall. Most of the recreation sites are urban recreation resources, so the above-mentioned recreation sites were used as the scope of the survey on urban smart tourism and competitiveness. In addition, the number of visitors to Yilan's recreation sites was 4,863,037. The more representative recreation sites are Dongshan River Ecoark, National Center for Traditional Arts, Qingshui Geothermal Park, Meihua Lake Scenic Area, and Wufengqi Scenic Area. Most of them are rural recreation resources, so this study uses the above-mentioned recreation sites in Yilan County to conduct a survey on rural smart tourism and competitiveness. In addition, from the above-mentioned tourist arrivals, we can see that if the number of tourists in Taipei City and Yilan County is 22,873,159 and 4,863,037, respectively, in 2021, this study uses the formula $n=Z^2\text{-}p(1-p)/e^2$ to calculate the sample size for this study. Where n is the sample size, Z is the confidence level, p is the true proportion of the parent, and e is the tolerable error. As we do not know the p-value with certainty, we set p=0.5 to maximize the n-value. Therefore, a reliability level of 95% (Z=1.96) was used, an estimation error of 8% (e=0.05) was allowed, and a random sample size of 1/2 (p=0.5) was used. The calculated sample size was approximately 384. However, in view of the possibility of invalid questionnaires or respondents' refusal to respond, a random sample of 400 questionnaires were distributed in the urban and rural areas of Taipei and Yilan from July to September 2021, for a total of 800 questionnaires. Of these, 763 questionnaires were valid, representing a validity rate of 95%. The questionnaire consisted of three main sections: respondents' basic information, recognition of smart tourism, recognition of destination competitiveness, destination imagery, and behavioral mapping.

The questionnaire will explain the terms "attractiveness of smart attractions" in smart tourism and "core resources and attractiveness" in destination competitiveness, using a five-point Likert scale to measure the potential variables. The potential variables are measured on a five-point Likert scale and rated on a scale of 1 to 5. On a scale of 1 to 5, 1 being "strongly disapprove" to 5 being "strongly approve." Descriptive statistics of the relevant basic information are shown in Table 1. In terms of gender, the majority of respondents in urban areas were male, accounting for 55.6%, and the majority of respondents in the age group of 21-30 years old, accounting for 62.1%. The majority of respondents were university graduates (67.3%). The occupation was mostly in the service sector, accounting for 39%. The majority of respondents (29.4%) had an income of NT$ 30,001 to 40,000. In terms of gender, the majority of rural workers were male, accounting for 62% of the total. The majority of respondents were aged between 21 and 30, accounting for 52%. The majority of respondents were university educated (60%). The occupation was mostly in the service sector, accounting for 25%. The majority of people with income between NT$ 30,001 to 40,000 (24%). As for the urban smart tourism indicators, "accessibility" scored the highest score of 4.29, followed by 4.28 for smart package service and 4.23 for smart convenience facilities. As for the rural smart tourism indicators, 4.27 marks for "Smart Package Service" scored the highest, 4.25 marks for "Smart Accessibility" ranked second, and 4.19 marks for "Attractiveness of Smart Attractions" ranked third. In terms of the competitiveness of urban destinations, the highest score was 4.51 for "supporting factors," followed by 4.41 for "tourism management" and 4.36 for "tourism services and facilities." As for the perceived competitiveness of rural destinations, the highest score was 4.42 for "supporting factors," followed by 4.37 for "destination management" and 4.33 for "tourism services."

Table 1 Descriptive Statistics of Respondents in Urban and Rural Destinations

Sex	No. for the urban area	Percentage for the urban area	No. for the rural area	Percentage for the rural area
Male	212	55.6%	236	62.0%
Female	170	44.4%	145	38.0%
Age	No. for	Percentage for the	No. for	Percentage for the

	the urban area	urban area	the rural area	rural area
12~20 years old	25	6.5%	28	7.3%
21~30 years old	237	62.1%	198	52.0%
31~40 years old	67	17.6%	79	20.7%
41~50 years old	32	8.5%	28	7.3%
51~60 years old	15	3.9%	30	8.0%
61~70 years old	5	1.3%	13	3.3%
71 years old and above	0	0%	5	1.3%
Education Level	No. for the urban area	Percentage for the urban area	No. for the rural area	Percentage for the rural area
Junior High	0	0%	3	0.7%
Senior High	25	6.5%	56	14.7%
University	257	67.3%	229	60.0%
Graduate School or above	97	25.5%	97	25.3. %
Average Monthly Personal Income	No. for the urban area	Percentage for the urban area	No. for the rural area	Percentage for the rural area
NT$20,000 and below	65	17.0%	33	22.0%
NT$20001~30000	57	15.0%	23	15.3%
NT$30001~40000	112	29.4%	36	24.0%
NT$40001~50000	57	15.0%	21	14.0%
NT$50001~60000	32	8.5%	6	4.0%
NT$60001 and above	57	15.0%	31	20.7%
Occupation	No. for the urban area	Percentage for the urban area	No. for the rural area	Percentage for the rural area
Manufacturing industry				
Freelance Industry	42	10%	76	20%
Service Industry	5	1%	13	3%
Military Personnel, Public	147	39%	97	25%
Servants, or Teacher	52	14%	43	11%
Retiree	2	1%	13	3%
Business	60	16%	43	11%
Agriculture, Fisheries &	5	1%	13	3%
Livestock	62	16%	74	19%
Student	2	1%	3	1%
Medical Industry	2	1%	8	2%
Art Related Industries				

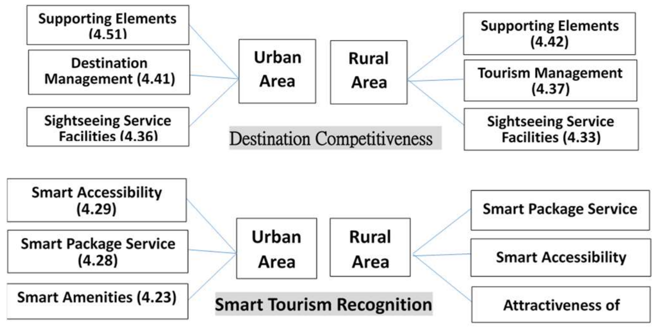

Figure 4. Top three perceived competitiveness of smart tourism and destinations in terms of urban-rural differences

4.2 The Interplay between Urban and Rural Smart Tourism and Destination Competitiveness

In order to understand the relationship between urban and rural smart tourism and destination competitiveness, and whether smart tourism and destination competitiveness affect destination imagery and behavioral intentions, this study adopts a partial least square structural equation.

4.2.1 Partial Least Squares SEM (PLS-SEM)

This study used Partial Least Squares SEM (PLS-SEM) with the statistical software Smart PLS 3 (Ringle, Wende & Becker 2015) and estimation models for the analysis. Unlike the old covariance-based structural equation modeling (CB-SEM), PLS-SEM is a multivariate method for estimating pathway models with potential variables for data that are different from the actual conditions, such as the need to meet the requirements of normative assignments and large sample sizes (Hair et al., 2017; Henseler et al., 2016; Sarstedt et al., 2011). Due to its broader use and less data-limited nature, this method has become an increasingly common analytical tool in market research and social sciences (Hair et al., 2012). In the PLS-SEM model, the measurement model is assessed for indicator reliability, construct reliability, Convergent Validity, and Discriminant Validity (Hulland, 1999; Hair, et al., 2014); In terms of reliability, the standardized factor loading (SFL) for observed variables is generally at least 0.7 in order to examine the explanatory power of the factors (Hair et al., 2014). However, in practice, this is not easy to achieve. Therefore, Hulland (1999) suggests that a value greater than 0.5 would be acceptable (Chan, 2018); In the group reliability section, the CR value is between 0 and 1. A higher value means higher internal consistency, and the criterion must be greater than 0.7 for consistency (Fornell & Larcker, 1981; Hair et al., 2014); In the section on convergent validity, the average variance extracted (AVE) is the extent to which the variance in all measured variables in the latent variables can account for the latent variables. That is, the higher the AVE, the more the latent variable is explained by the variation in its measurement variables.

According to the Average Variance Extraction (AVE), this value should be 0.5 or higher to ensure acceptable astringency. However, for the AVE to be higher than 0.5 or above, it means that the factor loadings must all be higher than 0.7 or above. Therefore, an AVE of 0.36 or above can be considered marginally acceptable given the practical orientation of the data (Fornell & Larcker, 1981); Discriminant validity has been compared to traditional evaluation methods (cross-loadings and Fornell & Larker criteria), and in recent years the heterotrait-monotrait ratio (HTMT) has been preferred (Henseler, et al. 2015; Voorhees, et al., 2016). Henseler et al. (2015) suggest that the HTMT confidence interval between all constructs does not contain 1 in order to have discriminant validity. If the HTMT value is less than 0.9, then there is discriminant validity between the two reactivity constructs (Kuan-Yu Chen, 2018). In addition, structural fit (structural fit) is concerned with the magnitude of explanatory power, R2 (R square), and correction R2 (R square adjusted) can be used to explain the variance of potential variables, R2 will be between 0 and 1, but there is no certain threshold. In general, R2 values close to 0.25 are considered to have a slightly weak explanatory power; An R2 value close to 0.5 indicates a moderate explanatory power; An R2 value close to 0.75 indicates significant explanatory power (Hair et al., 2014); Furthermore, with regard to the impact indicator of exogenous variables on endogenous variables (f2), according to Cohen's (1998) principle for evaluating f2 values, 0.02< f2≦0.15 can be called a small effect. 0.15< f2≦0.35 can be called a medium effect. f2>0.35 can be a large effect (Kuan-Yu Chen, 2018).

4.2.2 Analysis of Research Results

From the analysis of the results (Tables 2 and 3), we found that the AVE values were above the threshold of 0.5, indicating that the mean explanatory power of the constructs was above 50% and that they were all convergent. The composite reliability (CR) values were all above the threshold of 0.7, indicating that the constructs were internally consistent and reliable; The Cronbach's alpha was also above 0.7; It can be observed that the negative loadings between the variables and the potential variables are all above 0.5, indicating that the indicators are of moderate confidence or higher; In addition, Table 4 shows that the HTMT values of all the constructs are less than 0.9, thus having discriminant validity. From the above analysis results, it can be known that the measurement models all have the threshold and requirements of reliability and validity, and the structural model classification will be carried out next to test the causal path relationship between the various aspects.

Table 2: Estimated parameters of the urban measurement model

Urban Construct	Index	Factor loadings	Cronbach's α	Combination reliability (CR)	Average Variance Extracted (AVE)	R^2 (Correction)
Smart Tourism	Attractiveness of Smart Attractions	0.887	0.939	0.953	0.804	
	Smart Accessibility	0.894				
	Smart Amenities	0.902				
	Smart Package Service	0.869				
	Smart Assistive Services	0.904				
Destination competitiveness	Sightseeing facilities	0.823	0.842	0.927	0.863	0.559 (0.553)
	Supporting Elements	0.909				
	Site Management	0.93				
	Situational conditions	0.935				
	Core resources and attractiveness	0.918				
Destination image	Perceived imagery	0.93	0.919	0.939	0.755	0.573 (0.570)
	Emotional imagery	0.858				
Behavioral Intentions	Attitude	0.873	0.928	0.954	0.873	0.807 (0.805)
	Subjective Specifications	0.88				
	Perceptual Behavioral Control	0.824				

Table 3: Estimated parameters of the rural measurement model

Rural Construct	Index	Factor loadings	Cronbach's α	Combination reliability (CR)	Average Variance Extracted (AVE)	R^2 (Correction
Smart Tourism	Attractiveness of Smart Attractions	0.925	0.946	0.959	0.822	
	Smart Accessibility	0.933				
	Smart Amenities	0.933				
	Smart Package Service	0.902				
	Smart Assistive Services	0.944				
Destination competitiveness	Sightseeing facilities	0.839	0.900	0.952	0.909	0.579 (0.573)
	Supporting Elements	0.918				
	Site Management	0.859				
	Situational conditions	0.885				
	Core resources and attractiveness	0.874				
Destination image	Perceived imagery	0.861	0.927	0.945	0.774	0.601 (0.598)
	Emotional imagery	0.951				
Behavioral Intentions	Attitude	0.915	0.930	0.955	0.877	0.841 (0.839)
	Subjective Specifications	0.929				
	Perceptual Behavioral Control	0.927				

Table 4. Discriminant Validity Table (HTMT)

Urban Area				
	Smart Tourism	Destination image	Destination competitiveness	Behavioral Intentions
Smart Tourism				
Destination image	0.754			
Destination competitiveness	0.79	0.864		
Behavioral Intentions	0.585	0.555	0.792	

Rural Area				
	Smart Tourism	Destination image	Destination competitiveness	Behavioral Intentions
Smart Tourism				
Destination image	0.631			
Destination competitiveness	0.825	0.832		
Behavioral Intentions	0.645	0.899	0.788	

In terms of R^2 values for structural fitness, Table 2 and Table 3 show that smart tourism has a medium explanatory power for urban destination competitiveness and destination imagery and a high explanatory power for behavioral imagery. In villages, destination competitiveness has a medium explanatory power, while destination imagery and behavioral imagery have a high explanatory power. In addition, in the f^2 value (Table 5) section, both Smart Tourism→ Destination Competitiveness, Destination Imagery→ Behavioral Imagery, and Destination Competitiveness→ Destination Imagery show significant effects in the Urban section, while Smart Tourism→ Destination Imagery has a medium effect in the Urban section and a substantial impact on the Rural area.

Table 5. Table of f^2 effect measures

City				
	Smart Tourism	Destination image	Destination competitiveness	Behavioral Intentions
Smart Tourism		0.032	1.343	
Destination image				4.172
Destination competitiveness		0.551		
Behavioral Intentions				

Rural Village				
	Smart Tourism	Destination image	Destination competitiveness	Behavioral Intentions
Smart Tourism		0.041	1.505	
Destination image				5.270
Destination competitiveness		0.569		
Behavioral Intentions				

Furthermore, this study used bootstrapping to conduct 5000 path analyses and obtained statistical results to assess the model fit and the path coefficient of the PLS-SEM model (Dijkstra & Henseler, 2015).The results of the PLS structural model path analysis for smart tourism, destination competitiveness, destination imagery, and behavioral intent in urban areas are shown in Figure 4 and Table 6.In the sub-indicators the sub-indicators of Smart Tourism, Destination Competitiveness, Destination Imagery, and Behavioral Intentions all have significant interactions with each other. In the overall model, smart tourism has a significant impact on destination competitiveness, destination competitiveness has a significant impact on destination imagery, and destination imagery has a significant impact on behavioral intentions. Therefore, hypotheses H1-1, H3-1, and H4-1 can be verified as valid. However, smart tourism does not have an impact on destination imagery, so hypothesis H2-1 is not valid. From the above analysis, it can be seen that destination competitiveness is an essential component that mainly affects "destination imagery." Destination competitiveness also influences the behavioral intentions of visitors. However, smart tourism can be considered one of the components of destination competitiveness, which should be considered when considering the impact of destination competitiveness on destination imagery. Therefore, it is recommended that subsequent research and policymakers take smart tourism into account as a factor in determining the competitiveness of a destination in order to build and plan destination competitiveness in a more comprehensive manner.

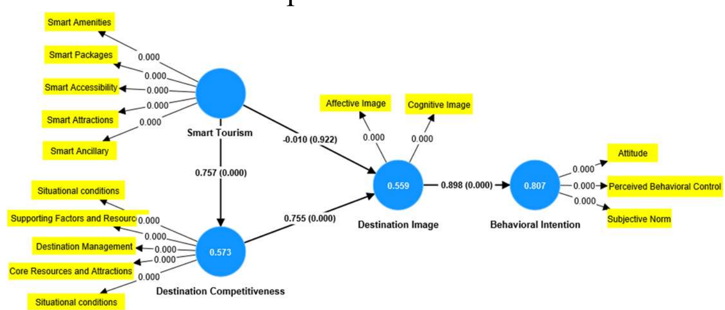

Fig 4. PLS structural model and path analysis of urban smart tourism and destination competitiveness

Table 6: Results of PLS structural model analysis of urban smart tourism and destination competitiveness

	Path coefficient (*β* value)	*T* value	*P* value
Smart Tourism -> Destination Imagery	0.010	0.098	0.922
Smart Tourism -> Destination Competitiveness	0.757	18.658	0.000***
Destination Imagery -> Behavioral Imagery	0.898	37.963	0.000***
Destination Competitiveness -> Destination Imagery	0.755	8.797	0.000***

Furthermore, the results of the path analysis of the PLS structural model for smart tourism, destination competitiveness, destination imagery and behavioral mapping in rural areas are shown in Figure 5 and Table 7. As with urban areas, the sub-indicators of Smart Tourism, Destination Competitiveness, Destination Imagery and Behavioral Intent all have a significant interaction with each other. In the overall model, smart tourism has a significant effect on destination competitiveness, destination competitiveness has a significant effect on destination imagery, and destination imagery has a significant effect on behavioral intentions. Therefore, hypotheses H1-2, H3-2 and H4-2 are valid; however, smart tourism does not have an impact on destination imagery, so hypothesis H2-2 is not valid.

The results for rural areas are consistent with those for urban areas. Destination competitiveness is an essential component of destination imagery, which in turn influences the behavioral intentions of visitors. However, smart tourism can be considered as a component of destination competitiveness and can be taken into account as a factor when considering the impact of destination competitiveness on destination imagery. It is therefore recommended that subsequent researchers and policymakers should consider smart tourism as a factor in destination competitiveness in order to build and plan destination competitiveness in a more comprehensive manner.

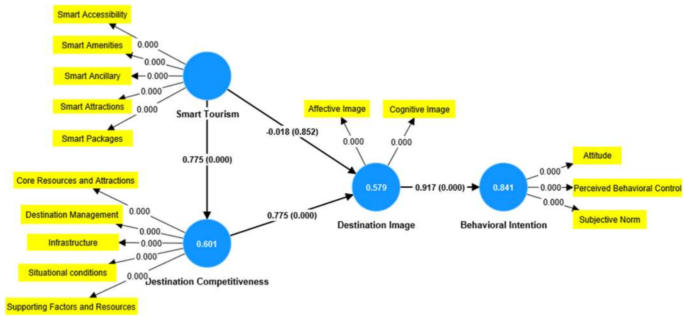

Figure 5. PLS Structural Model and Pathway Analysis of Rural Smart Tourism and Destination Competitiveness

Table 7. PLS Structural Model and Analytical Findings on Rural Smart Tourism and Destination Competitiveness

	Path coefficient (β value)	*T* value	*P* value
Smart Tourism Destination Imagery	0.018	0.186	0.832
Smart Tourism Destination Competitiveness	0.775	20.928	0.000***
Destination Imagery Behavioral Intentions	0.917	52.952	0.000***
Destination Competitiveness Destination Imagery	0.775	7.500	0.000***

Conclusions and Recommendations

This study begins by combining the indicators of smart tourism and destination competitiveness to understand the relationship between smart tourism and destination competitiveness, and whether smart tourism and destination competitiveness affect destination imagery and behavioral intent. The study also uses the Recreational Opportunity Sequence (ROS) to distinguish urban areas from rural areas and to explore whether there are differences. In addition to enabling more realistic planning, this study will explore elements that have not been explored in previous planning and research studies. In terms of recognition of urban smart tourism indicators, "smart accessibility" scored the highest; in terms of recognition of rural smart tourism indicators, "smart package service" scored the highest; In terms of recognition of destination competitiveness, both urban and rural areas scored the highest on "supportive factors." This means that health and hygiene conditions, tourist education, and ICT support functions are the top priorities for urban and rural destinations.

In terms of the interaction between smart tourism, destination competitiveness, destination imagery, and behavioral intention, smart tourism has a significant impact on destination competitiveness in both urban and rural areas, destination competitiveness has a significant impact on destination imagery, and destination imagery has a significant impact on behavioral intention.

However, smart tourism does not have an impact on destination imagery. Therefore, it can be concluded that destination competitiveness is a significant and essential component of destination imagery, which in turn affects the behavioral intentions of tourists. However, smart tourism can be considered as a component of destination competitiveness and is included as an element of destination competitiveness that affects destination imagery. It is recommended that subsequent research and policy-making bodies should include smart tourism as a critical consideration in enhancing destinations' competitiveness to construct and plan destination competitiveness in a more comprehensive manner.

In terms of future recommendations, as the factors in the Smart Tourism Indicators and Destination Competitiveness Indicators may be correlated, this study suggests that the weighting of the elements can be further calculated using the Analytical Network Process (ANP) method to prioritize and evaluate the two indicators. It is expected that this can be used as an essential reference in planning smart tourism indicators and destination competitiveness. In addition, the study will also use multi-objective programming (MOP) to construct a planning model for urban and rural smart tourism priority development subsidies, to weigh the balance between economic, social, and environmental aspects of the smart city orientation, as well as the perceived differences between tourists and residents, in order to understand the current situation of urban and rural tourism destinations. This study will conduct in-depth interviews with residents and tourists to understand the conflict between these two roles in smart tourism and then apply the developed planning model to conduct an empirical analysis to confirm the feasibility of applying the model in practice and to conduct a sensitivity analysis. The analysis results can be used as a resource for planning units to make reference to when planning for priority areas for urban and rural smart tourism development grants. Furthermore, in addition to tourists, destination competitiveness factors can be significantly influenced by the activities of stakeholders (local residents, accommodation owners, owners of tourist attractions, tourism service providers, local government representatives, etc.) (Luštický & Štumpf, 2021). Smart tourism also needs to address issues related to stakeholder knowledge, preferences, and values more broadly (Gelter, 2022; Pan et al., 2021). Therefore, it is recommended that subsequent studies should compare more stakeholders and analyze more different types of cities and villages in order to gain a more comprehensive understanding of smart tourism and destination competitiveness in urban and rural areas and to make more comprehensive policy planning and resource allocation.

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