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Interview

TechTalk with Dr. Kaye Chon: A Pioneer of Asian Paradigm in Hospitality and Tourism

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"Depending on how you define smart tourism, there are many applications already existing … I would like to define smart tourism at the micro-level, not necessarily transforming a city or destination."

In an interview with Journal of Smart Tourism (JST), titled as "TechTalk", Professor Kaye Chon (Dean and Chair Professor and Walter & Wendy Kwok Family Foundation Professor in International Hospitality Management in the School of Hotel and Tourism Management at the Hong Kong Polytechnic University) shared his view on smart tourism. The interview has been edited for length and clarity.

Q: How do you define smart tourism? Can you share your experience related to smart tourism?

A: I think we talked about smart tourism usually at the mega or macro-level. But there are many applications at the micro-level in operations or in businesses. Depending on how you define smart tourism, there are many applications already existing.

For example, a few years ago, when staying a hotel, we had to insert a card key to open the door. However, there is something called proximity access card. Now, we do not have to even insert the key, just scan the card. If it is difficult to find it in your handbag, we can scan the entire bag then that will open the door.

There have been many applications like this example. To my understanding, all these are smart tourism applications. I would like to define smart tourism at the micro-level, not necessarily transforming a city or destination.

Q: There are some courses related to smart tourism in the School of Hotel and Tourism Management (SHTM) at The Hong Kong Polytechnic University (PolyU). What led you to make that decision?

A: A variety of information technologies have been evolving very fast in the hospitality and tourism industry. Along with several regions, Hong Kong becomes one of the fields of experiment in smart tourism development. Researchers, practitioners, and policymakers in Hong Kong are paying greater attention to smart tourism with a view to enhancing the competitiveness of the region as an international destination.

It is very important for us to continuously monitor the changes in the environment and then align our strategies with them. In the last 20 years since I was in SHTM, we revised our curriculum several times according to those changes, so this led us to make such decisions.

Q: Do you consider further developing the smart tourism-related courses, such as create a degree of smart tourism?

A: We are not necessarily aiming to develop smart tourism experts. Rather, we plan to make it as a specialization which can be chosen by students. Still, they are studying hotel and tourism management but understanding smart applications. That’s an aim of our plan for the upcoming bachelor’s degree.

Q: Which skills and knowledge do you think important for students to learn when they study ‘smart tourism’?

A: If students have a good understanding of artificial intelligence (AI), big data analytics, robotics, and digital transformation, do you believe that they would have a huge advantage in our field? If you ask me what is job in smart tourism, to be honest, I cannot think of one single job in that area. Although it sounds like this is a very smart industry, students have to think strategically.

For example, the understanding of AI can be associated with sales management. Let’s imagine there are two phone calls coming in at the same time. One person wants to make a reservation for two people for dinner. Another person wants three. Our brain has been trained to think that three is better than two. There’s 33% more revenue. However, this can be wrong when demand is so high. Since most tables are four people, the reservation for three people leads the restaurant to waste the one seat. On the other hand, the reservation for two allows it to avoid the wasting because the restaurant can simply divide the table into two parts and set it to two parties of two people each, increasing revenue by 25%. If you incorporate this logic into the reservation algorithm, you would create a smarter system.
inferred in this example, students have to think about a functional profession.

Q: As the last question, what advice do you want to give to this newly launched Journal of Smart Tourism?

A: In terms of journal development, you have to have a clear roadmap and devote yourself to monitoring the trends, and then screening the papers with a systematic review process.

On the other hand, the positioning of your journal will be the key: what would be the perception of people writing a paper in this journal? As mentioned in the first answer, I think smart tourism is much broader than what many people may think. If the topics are broadly set by including smart tourism and hospitality applications, perhaps there will be a greater audience.
Empirical Research Article

Research Progress and Development of Technology in Tourism Research: A Bibliometric Analysis

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Abstract

The interaction between technology and tourism has been a dynamic research area recently. This study aims to review the progress and development of technology in tourism research via a bibliometric analysis. We derive the source data from the Web of Science (WoS) core collection and use CiteSpace for bibliometric analysis, including countries, institutions, authors, categories, references, and keywords. The analysis results are as follows: i) The number of published articles on the role of technology in tourism has increased in recent years. ii) Technology-related articles in tourism are abundant in Tourism Management, Journal of Travel Research, and Annals of Tourism Research. iii) The countries with the most contributions are China, the US, and the UK. The most active institutions are the Hong Kong Polytechnic University, University of Central Florida, Bournemouth University, University of Queensland, and Kyung Hee University. iv) The reference analysis results identify eight extensively researched topics from the most cited papers, and the keyword burst analysis results present an emerging trend. This study identifies the effect and development of technology in tourism research. Our findings provide implications for researchers about the current research focus of technology and the future research trend of technology in the tourism field.

Keywords

technology; tourism; visualization; CiteSpace; bibliometric analysis

1. Introduction

In tourism, technology is a catalyst for development as it determines the strategy and competitiveness of tourism destinations (Buhalis & Law, 2008). With the advancement of technology, smart tourism has developed dramatically, which led to various possibilities. In tourism research, scholars paid close attention to the application of different technologies, such as cloud computing (Zhou, Xu, & Kimmons, 2015), big data (Yang et al., 2020), artificial intelligence (AI; Li, Bonn, & Ye, 2019), robot (Zhong, Yang, Rong, & Li, 2020), augmented reality (AR; Poux, Valemois, Mattes, Kobelt, & Billen, 2020), and virtual reality (VR; Fang & Lin, 2019). Their efforts have created a new development space and provided powerful technical wisdom for the current tourism industry.

Reviewing literature is critical to understand the topic in-depth in the academic field (Tranfield, Denyer, & Smart, 2003). The unprecedented growth of knowledge caused by the development of information technology makes it difficult for academic researchers around the world to be informed of the specific knowledge in a certain topic. Being faced with the rapid growth of massive literature, it is not easy for academic researchers to understand research progress accurately and timely only through traditional manual retrieval methods. As a result, how to grasp and understand the knowledge structure and evolution process of a certain research field in a scientific, efficient and intuitive way has become necessary and important for both academic researchers and industry practitioners.

Bibliometric analysis is originated from the field of library and information science. Driven by the rapid development of computers and Internet, bibliometric analysis has gradually attracted the attention from the scientific community (Bar-Ilan, 2008). Bibliometric analysis can be conducted in many different ways such as analyzing bibliographic data with quantitative network analysis to identify the structure of research (Dzikowski, 2018). Scientific knowledge mapping, in a form of new development of scientific metrology and informetrics, can reflect the complex domain of modern science and technology knowledge through data mining, information processing, and graph drawing. Scientific knowledge can assist researchers in understanding the position of their research in a certain research field and make it easier for them to find new research trends/topics in an effective way (Liu, Chen, & Hou, 2008).

Many studies focusing on specific technologies in the hospitality and tourism have been published in recent years (Mariani, Baggio, Fuchs, & Höpken, 2018; Poux et al., 2020; Shao, Chang, & Morrison, 2017; Tussyadiah, 2020; Yang & Chew, 2020). However, a comprehensive overview of technology development in tourism using bibliometric and knowledge mapping methods is still limited. Hence, the present study applied bibliometric analysis and used the knowledge mapping tool CiteSpace to...
analyze and explore technology development in tourism over the past 30 years (1991–2020) visually by answering the following research questions. i) What are the discipline distribution and main source journals relating to technologies in tourism research? ii) Which are main contributors of relevant research field in terms of countries, organizations, and authors? iii) What are the critical research works and their knowledge foundation in this field? and iv) What are the research hotspots and emerging trends in this area?

2. Literature Review

2.1 Cloud Computing and Big Data in Tourism Research

Cloud computing and big data have become significant parts of modern systems, especially in information processing and intelligent analytics (Dong, Wu, & Gao, 2019). In recent years, big data have provided opportunities in many research fields. However, the storage, transmission, and mining of large amounts of data pose challenges to the current technical foundation. With the development of parallel computing and distributed computing, cloud computing has offered basic technical support concerning problems brought by shared computing resources (Yang, Huang, Li, Liu, & Hu, 2017). In particular, cloud computing has spawned a series of big data processing tools, such as GFS (Ghemawat, Gobioff, & Leung, 2003), BigTable (Chang et al., 2008), and MapReduce (Dean, Ghemawat, & Mehta, 2008), which provide powerful technical support for the efficient processing of big data. In tourism research, the content of cloud computing and big data mainly includes: predicting the development of different hotels (Li, Lu, Xu, & Sun, 2020), exploring the information fusion in the intelligent park (Yu, Song, & Zhang, 2019), monitoring tourist flow in scenic spots (Qin et al., 2019), analyzing and predicting the popularity of tourist destinations (Chen, Law, Xu, & Zhang, 2020), managing tourist destinations using data mining techniques (Zhang & Dong, 2021), reflecting tourists’ views on the services through mining tourism blog data (Shao et al., 2017), and designing real-time route recommendation systems for tourists (Mehmood, Ahmad, & Kim, 2019). Smart tourism depends on big data, and the ultimate goal is to extract information from big data for accurate smart tourism planning (Gretzel, Sigala, Xiang, & Koo, 2015). By collecting, analyzing, and interpreting the big data, smart tourism management can provide personalized experiences for tourists (Buhalis & Amaranggana, 2015).

2.2 AI in Tourism Research

For tourists to experience world-class tourism, the tourism industry needs to provide various artificial services to meet their physiological, psychological, and social needs. AI offers personalized services to users, and at present, researchers in the field of tourism and hospitality started to investigate AI, robotics, and other related fields (Tussydjah, 2020). They mainly focused on AI applications in tourism and the possible development direction and influence of AI on tourism in the future (Ivanov & Webster, 2020; Murphy, Gretzel, & Pesonen, 2019; Murphy, Hofacker, & Gretzel, 2017; Tung & Law, 2017). In smart tourism research, Tsaih and Hsu (2018) provided a conceptual framework for digital management strategy. Wang Kumar, et al. (2020) discussed the capabilities of 5G and AI in realizing the potential of the Internet of Things for smart tourism. Murphy et al. (2019) proposed 11 robot capabilities that can influence anthropomorphism and eventually shape HRI (Human–Robot Interaction). In summary, efficient data collection based on 5G technology and intelligent data processing using AI technology will be of great significance to the development of intelligent tourism technology (Wang Kumar, et al., 2020).

2.3 VR and AR in Tourism Research

In recent years, the rapid development of VR and AR technology has provided highly immersive interactive operations. They offer new ways to present the information required by users in multiple spatial and temporal dimensions. Thus, they have great potential application for the further development of tourism (Gretzel, Zhong, & Koo, 2016). VR technology can create an interactive experience, providing users a strong sense of immersion (Hemanth, Kose, Deperlioglu, & de Albuquerque, 2020). AR allows different interaction styles, which can trigger curiosity and interest from a user-centered perspective (Galalis, Gavalas, Kasapakis, Pantziou, & Zaroliagis, 2016). When VR and AR just began to develop, their application was mainly for gaming and entertainment (Zyda, 2005). After a few years, many academic and industrial fields started to explore deeper needs to solve real-world problems (Guttentag, 2010; Ong & Nee, 2013). In tourism research, Guttentag (2010) suggested that VR offers opportunities to tourism researchers and professionals in several directions, including planning and management, marketing, education, accessibility, and heritage preservation. Regarding application, Paliokas et al. (2020) proposed an AR quiz game designed to increase the time museum visitors interact with artifacts, which offered a playful way to gain knowledge and travel in a 3D space.

3. Methodology

3.1 Data Sources

The selection of databases is a crucial issue in bibliometrics research (Martens, Lacerda, Bellfort, & de Freitas, 2016). Thomson Reuters developed Web of Science (WoS), an accurate, prestigious, and well-known database providing widely accepted high-quality scientific publications (Olawumi & Chan, 2018). Thus, this study used the WoS core collection database. The citation database was set as SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, and ESCI, as the sample data source determines the reliability of the data retrieved.

This study focused on different technologies, including cloud computing, big data, the Internet, AI, and VR and AR technology, as previously mentioned in Section 2. The data retrieval strategy used for the search included the following terms: (TI = ["tourist*" OR "tourism" OR "traveler*" OR "travel" OR "hotel*" OR "restaurant*" OR "hospitality]) AND (TS = ["smart*" OR "technology*" OR "digital" OR "cloud computing" OR "big data" OR "web*" OR "online" OR "Internet" OR "artificial intelligence" OR "robot*" OR "virtual reality" OR "augmented reality"]). To ensure the sample accuracy, we defined the retrieved results by document types, including "ARTICLE," "PROCEEDINGS PAPERS," and "REVIEW." We excluded the papers written in languages other than English and then saved and output the retrieved results in text format. Each document contained authors, institutions, keywords, abstract, date, references, and other related information for analysis. We collected the data in January 2021, with an initial data retrieved of 12,447 articles from WoS. However, only find only a few publications could be found from 1958 to 1990 (i.e., fewer than one publication each year). Thus, data were retrieved from 1991 to 2020, with a total of 12,422 articles. Specifically, through adopting "Duplicates Removal" function in CiteSpace, duplicated articles were discarded. In addition, "Article," "Review," and "Proc." functions were selected to clean the data. As a result, 12,422 articles were reserved for further analysis.

3.2 Analytical Tools

Many science mapping tools, including VOS viewer (Nazir et al., 2021; Ye, Ye, & Law, 2020), CoPalRed (Bailón-Moreno,
Jurado-Alameda, & Ruiz-Baños, 2006), Gephi (Johnson & Samakovlis, 2019), and CiteSpace (Fang, Yin, & Wu, 2018; Yang et al., 2020), have been available for bibliometric analysis. CiteSpace detects the emerging trends and abrupt changes in the scientific literature (Chen, Hu, Liu, & Tseng, 2012). Thus, it can present the panorama and reorganization of knowledge structure intuitively. On this basis, we employed CiteSpace 5.7.R1 to analyze categories, countries, institutions, authors, references and keywords, and research hotspots. We used the following parameters: Period: 1991–2020, Time Slice Length = 5; Node Type: Option based on analysis; Selection Criteria: Top 48 per slice; Pruning: Pathfinder, pruning sliced networks, and the merged network; others were default settings. More detailed parameters are available at the upper left corner of each knowledge map.

4. Analysis and Results

4.1 Annual Publication Trend

On the basis of the retrieved data, the analysis covered articles published from 1991 to 2020. Figure 1 is a bar chart showing the annual publication trend of related studies. The tendency of annual publications showed an upward trend from 1991 to 2020. Specifically, the increased rate of publications was stable from 1991 to 1997. From 1997 to 2007, the number of publications gradually increased. From 2008 to 2020, the number of publications grew quickly, indicating that tourism technology was a hot topic in the past 12 years. The number of tourism publications has grown rapidly since 2008 could be attributed to the rapid development of ICTs (Information and communication technologies) such as smart phones (late-2000s) and social media platforms (mid-2000s). In addition, service delivery in the tourism industry in 2008–2020 experienced the shift from electronic service (e-service) to mobile service (m-service) (Leung, 2019). As a whole, the span of the identified records was 30 years. They included 8,005 articles, 3,866 proceedings papers, and 545 review papers, as shown in the database. The concise statistic presented a general overview from final retrieval results, providing researchers an understanding of the overall trend of tourism technology development.

4.2 Category Analysis

The purpose of this section is to identify the major disciplines involved in tourism research in order to provide an overall picture of technology development of tourism research. Following the discipline system of WoS, one publication might cover one or more fields. Thus, the number of publications may be more than the number of total recorded publications every year. The 12,416 articles about technology in tourism research could be divided into 222 research directions to show the interdisciplinary characters. Figure 1 presents the trend of article output in the top 10 WOS categories from 1991 to 2020 with more than 735 publications. The stacking area map shows the emerging trend of every research area in each year. Figure 2 provides more detailed information about the number of publications every year in each category. Most studies belonged to Hospitality, Leisure, Sport, and Tourism, with 4,106 articles accounting for 31.74%. Moreover, Management (1,837; 14.20%), Business (1,107; 8.56%), Information Systems under Computer Science (1,044; 8.07%), Environmental Studies (898; 6.94%), Theory and Methods of Computer Science (864; 6.68%), Electrical and Electronic Engineering (802; 6.20%), Transportation Science and Technology (797, 6.16%), Economics (745, 5.76%), and Management (218). In 1991, most studies belonged to Information Systems under Computer Science (128), Theory and Methods of Computer Science (128), and Economics (96). In 2018, studies focusing on Business (131), Transportation (99), and Transportation Science and Technology (97) were rampant. In 2017, papers published in Electrical and Electronic Engineering (98) reached the highest number of publications in 30 years. In general, from 2017 to 2020, the number of studies in each of the above areas was the highest. Relevant studies about tourism technologies were extended to business, management, computer science, environment, economics, and transportation, showing the characteristics of multi-direction integration and human-oriented orientation.
4.3 Journal Analysis

Academic journals are important outlets for research dissemination in a certain research field. Through the analysis of the source journals, the core journals in this field can be found, which can assist researchers to be informed of the research scope and research goal efficiently (Zhao, Tang, & Zou, 2019). We analyzed the most active journals and their impact (five years), as shown in Figure 3. Tourism Management accounted for the most senior research with 346 articles and the highest number of 5,314 citations. The second most prolific journal is Journal of Travel Research (3,412), followed by Annals of Tourism Research (3,351). Our findings confirmed that journals with high impact factors might have high quotation frequencies. Most journals were from Elsevier Ltd. in the UK and SAGE Publications Ltd. in the US.

4.4 Country Collaboration Networks

As the number of national publications can reflect a country’s contribution to the research field, country collaboration networks were analyzed. Figure 4 presents the network of collaborating countries consisted of 66 nodes and 64 links between 1991 and 2020. The thinness of the links between countries implies the level of cooperation. The top 10 countries listed on the right-hand side made the major portion of contributions. From 1991 to 2020, Chinese institutions contributed the most to this research field, with 2,968 published articles. However, its centrality was less than in other countries. The US was the second-largest contributor, with 2,472 papers published, followed by England (852), Spain (805), and Australia (709). Except for China, the major nodes in Asia were South Korea (371), India (295), and Malaysia (291), ranking 7th, 9th, and 10th in publication counts. European countries made significant connections with other countries, such as England, Spain, and Italy, as shown by the links in Figure 4.

Fig. 3. Top 10 active journals based on the frequency of citations
Collaboration Network of Different Institutions

As cooperation between/among institutions is a key to promote the overall strength of the academic organizations and it is also a critical way to realize complementary scientific research resources for knowledge sharing, which the analysis results can reflect the research status in a certain field (Gu, Li, Li, & Liang, 2017). Figure 5 is a collaboration network, with 178 institutions and 98 collaboration links between 1991 and 2020. The top 10 institutions with the most contributions to the total outputs are presented on the right-hand side of Figure 5. With 404 publications, the Hong Kong Polytechnic University topped the list, followed by the University of Central Florida (145), Bournemouth University (95), and Kyung Hee University (95). China was the top contributor in related fields with two institutions (the Hong Kong Polytechnic University and Sun Yat-sen University, ranking 1st and 9th, respectively). The list also includes three institutions from the US (University of Central Florida, Pennsylvania State University, and the University of Nevada, ranking 2nd, 8th, and 10th, respectively), two institutions from the UK (i.e., Bournemouth University and the University of Surrey), and two institutions from Australia (i.e., the University of Queensland and Griffith University). The contribution of institutions was in direct proportion to the contribution of countries.

Author Contribution Analysis

The author analysis is considered an effective way to learn the connections between academic organizations and to figure out the main contributors in a certain field. Figure 6 is an author collaboration network of contributions to tourism technology, with 309 authors and 214 collaboration links. The top 10 authors based on frequency are displayed on the right-hand side of Figure 6. The results show that Rob Law contributed the most to the field of tourism research about technology. His affiliation is School of Hotel and Tourism Management, the Hong Kong Polytechnic University, focusing on information and communications technology research in hospitality and tourism (Law, Leung, & Chan, 2019; Leung, Law, van Hoof, & Buhalis, 2013) and mobile technology in hospitality and tourism (Chen et al., 2020). Dimitrios Buhalis is one of the major scholars who focused on electronic tourism (e-tourism: Buhalis & Law, 2008; Buhalis & Wagner, 2013) and smart tourism and hospitality (Buhalis & Amaranggana, 2015; Buhalis & Leung, 2018). Buhalis is the director of the e-Tourism Lab at Bournemouth University in the UK. Ulrike Gretzel is a notable author in smart tourism and hospitality research. Her research focus includes smart tourism development (Gretzel et al., 2015), smart destination brands (Gretzel & Collier de Mendonça, 2019), and e-tourism (Gretzel et al., 2020). Most authors in the top 10 list have affiliations in the department/school relating to the tourism, management, and marketing, associated with institutions in Figure 6. Indeed, the authors in the top 10 list have close research collaborations in tourism.

Reference Analysis

To acquire the knowledge foundation of relevant research, we adopted co-citation analysis to show the fundamental research achievements in different periods. The nodes are labeled, as shown on the left-hand side of Figure 7. It includes the name of the first author and the publication year of the article. The top 10 article nodes with significant academic influence are shown on the right-hand side. On the basis of the keywords and the number sorted in Figure 7, the most cited papers covered the following eight topics: i) Word-of-mouth (Number 3, 7, 8, 9, and 10), ii) Online reviews (Number 3, 8, and 9), iii) User-generated content and big data (Number 5, 6, and 10), iv) Social media (Number 2, 4, and 10), v) Marketing (Number 1, 2.7), (vi) Web and Internet (Number 1 and 4), (vii) Travel choice and consumer choice (Number 3 and 8), and (viii) Online bookings/Hotel bookings (Number 3 and 5). To some extent, these topics can reflect the research focus in this field. In general, the top 10 articles are mainly review articles (1, 4, and 9) and articles that studied the effect of technology on tourism (2, 3, 5, 7, and 8).
Fig. 5. A visualization of the institution collaboration network.

Fig. 6. Visualization of author collaboration network and the top 10 authors.

Fig. 7. Visualization of co-citation network and top 10 most cited papers with frequency.

1* Progress in information technology and tourism management: 20 years on and 10 years after the Internet—The state of e-Tourism research (Bulbulia & Law, 2008).
2* Role of social media in online travel information search (Xiang & Gretzel, 2010).
3* The impact of online reviews on hotel booking intentions and perception of trust (Sparks & Browning, 2011).
4* Social Media in Tourism and Hospitality: A Literature Review (Leung et al., 2013).
5* The influence of user-generated content on traveler behavior: An empirical investigation on the effects of e-word-of-mouth to hotel online bookings (Ye, Law, Gu, & Chen, 2011).
6* Smart tourism: Foundations and developments (Gretzel et al., 2015).
7* Electronic word-of-mouth in hospitality and tourism management (Litvin, Goldsmith, & Pan, 2008).
8* Tried and tested: The impact of online hotel reviews on consumer consideration (Vermeulen & Seegers, 2009).
9* New consumer behavior: A review of research on e-WOM and hotels (Serra Cantallops & Salvi, 2014).
4.8 Research Hotspots and Emerging Trend Based on Keyword Burst Analysis

Figure 8 displays the top 40 keywords with the strongest citation bursts. Among them, keywords with the longest citation bursts period are "design" (2001–2014, 14 years), "Internet" (2000–2013, 14 years), "system" (1996–2008, 13 years), "e-commerce" (2001–2013, 13 years), and "GIS" (1998–2010, 13 years). From 1996, keywords with strongest citation bursts began to show, including "knowledge management," "web," "e-business," "China," "Internet marketing," "semantic web," "ease," "consumption," and "sustainable tourism." Starting from 2004, "travel agency," "e-tourism," and "network" started to burst. "Smart tourism," "review," and "big data" are the most recent hot topics discussed by authors in tourism and hospitality research concerning technologies with high citation burst, as shown in Figure 8. Moreover, the burst time is associated with the most cited articles shown in Figure 8 for tourism technology (Gretzel et al., 2015; Leung et al., 2013; Serra Cantallóps & Sabri, 2014).

Figure 9 is a timeline generated to visualize the co-occurring keywords from 1991 to 2020. Each node represents cited keywords, and the links show the keyword co-citation relationships. To produce a unique result and wide coverage, we used log-likelihood ratio (LLR) as one of the three algorithms (LSI, LLR, and MI) in CiteSpace (Jin, Ji, Li, & Yu, 2017). To generate high-quality clustering with intraclass similarity and inter-class similarity, we deemed the LLR test suitable for our study (Wang, Ma, et al., 2020). On the top of Figure 9, the gradual color pattern indicates a change between each time slice. The deep purple represents the beginning of the study (1991–5), and the yellow color on the right-hand side denotes the end of the study period (2016–20). In the analysis, we screened the top 13 largest clusters. The results showed the top 13 clusters, including "#0 big data," "#1 hotels," "#2 information technology," "#3 teleworking," "#4 website," "#5 reliability," "#6 online reviews," "#7 trust," "#8 loyalty," "#9 online puncher," "#10 system," "#11 managers perceptions," and "#12 consumption." The sequence of the clusters and the time of nodes shown on every horizontal axis intuitively present the rise and fall of specific research content.

### Top 40 Keywords with the Strongest Citation Bursts

<table>
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<td>2008</td>
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<td>navigation</td>
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<td>2005</td>
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<td>2005</td>
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<td>GIS</td>
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<td>Internet</td>
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<td>e-commerce</td>
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</table>

Fig. 8. Top 40 keywords with the strongest citation bursts
4.9 Changes That Technology Has Brought to Tourism and Future Research Directions

From the demand perspective, technologies enriched the number of options for consumers in hospitality and tourism. Smartphones that are being used today provide the opportunities for consumers to access the Internet anytime and anywhere. Social networking services (SNS) such as Facebook, Instagram and Twitter provide platforms for tourists to get advice from online reviews or share their experience with others. SNS engagement can also have a direct impact on electronic word-of-mouth (e-WOM) of the intentions of users (Okazaki & Yagüe, 2012). In the hotel scene, technological advancements of artificial intelligence (AI) play an important role in enhancing consumers’ satisfaction and experience, and stimulating consumers’ motivation to engage in the service encounters. From the suppliers’ perspective, technologies applied in hospitality and tourism improve the service quality and help proprietors to save costs (Business Wire, 2018). Based on the above analysis, several future research directions are summarized from recent studies:

- Security and privacy problems in AI systems (Ivanov & Webster, 2020; Tussyadiah, 2020)
- Customer’s acceptance of different technologies and intentions to use different technologies in various service scenarios (Go, Kang, & Suh, 2020; Lin, Chi, & Gursoy, 2020)
- The coordination problems of multi-agent systems in smart tourism and the establishment of ecosystem (Buhalis & Leung, 2018)
- Applications of AR technologies in hospitality and tourism (Paliokas et al., 2020) and their impact on consumer’s behaviors and psychology
- The role of technologies during epidemics and pandemics in tackling complex problems (Pillai, Haidorai, Seo, & Kim, 2021)

4.10 Implications

This paper can assist academic researchers in exploring ideas from the massive research data of predecessors and understanding current research situation in the related fields. The use of CiteSpace to excavate the structure and development of knowledge in a visual way can assist in presenting the research hot spot and emerging trend through reference analysis and keyword burst analysis. In addition, the co-occurrence analysis of countries, authors and institutions efficiently detect the contribution and cooperation between different academic organizations can be regarded as important indicators to evaluate the level and quality of present research status. Furthermore, it is of great importance for academic researchers to select articles with high quality, confirm research objects rapidly, and expand the depth and breadth of certain research area.

5. Conclusions and Future Research

This study presents the role and development of technology in smart tourism research using a bibliometric analysis method. It aims to provide researchers the information on the development of tourism technology, current research focus, and the trend in tourism technology. We draw the following conclusions from the bibliometric analysis results of research on technology in smart tourism:

Scholars focused on the role of technology in tourism, and the number of related papers published has been increasing in recent years. From 2007 to 2020, relevant papers have grown rapidly, reflecting the interaction between technology and tourism. Tourism Management, Journal of Travel Research, and Annals of Tourism Research, as leading journals in tourism research, include more research about tourism-related technology than other journals. In terms of contributions, the most active institutions include the Hong Kong Polytechnic University, the University of Central Florida, and Bournemouth University. Researchers in these institutions (e.g., Rob Law, Ulrike Gretzel, and Dimitrios Buhalis) have close connections in tourism technology and greatly contributed to the topic, as reflected in the high co-citation frequency of their papers (Buhalis & Law, 2008; Xiang & Gretzel, 2010).

We also conducted reference analysis to identify the most
cited papers. Our findings show eight topics frequently discussed by authors. These topics include word-of-mouth, online reviews, user-generated content and big data, social media, marketing, web and Internet, travel choice and consumer choice, and online bookings/hotel bookings. In general, the top 10 articles are mainly review articles and those related to the effect of technology on tourism. Through keyword burst analysis, we also find research hotspots and emerging trends. The period of the co-occurrence keywords displayed in Figure 9 shows the top 13 clusters, including “big data,” “hotels,” “information technology,” “teleworking,” “website,” “reliability,” “online reviews,” “trust,” “loyalty,” “online puncher,” “system,” “manager perceptions,” and “consumption.” However, our study has a limitation. Technologies that were included in the present study is the one that have been widely adopted in tourism, such as cloud computing, big data, Internet, AI, and VR and AR technology, and do not include those rarely applied in tourism. In addition, technology adoption in other industries such as automotive industry was not considered in the present study. Moreover, the method that was adopted in the present study was purely quantitative. Future research can consider other recent technologies, such as quantum computing, and how technology adoption in other disciplines change the use of technology in tourism to investigate big data and brain-computer interface technology. Furthermore, a mixed approach can be adopted in the future to explore potential research direction and help study tourist behavior.

Declaration of competing interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Adoption of Smart Sustainability Performance Measurement System (SPMS) in Hotels and Variations across Ratings, Reviews, and Operational Efficiency Scores

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Abstract

Hotels have recently started to implement enterprise information systems to measure and report sustainability indicators in a smart manner. However, a complex ownership structure in a hotel chain prevents full smart systems adoption at the individual property level. This study explores how a smart sustainability performance measurement system (SPMS) for waste management adoption correlates with customer ratings, customer reviews, operational efficiency scores, and between franchised and corporate-managed properties. We derive insights from the secondary data constructed from multiple sources for a large multinational hotel chain hotel. The findings suggest that hotels that adopt SPMS have better operational efficiency scores and more customer reviews. Within the hotels that adopted SPMS, corporate-managed hotels have a lower level of ratings than franchised hotels, but they have higher operational efficiency scores and more reviews. We discuss research implications for the concept of smart tourism and hotel management literature and managerial implications.

Keywords

SPMS; hotel performance; hotel ownership; sustainability management; smart hotel

1. Introduction

Firms are making an effort to improve their sustainability management performance to address climate change challenges (Dahlmann, Branick, & Brammer, 2019). Waste management, an essential aspect of sustainability management, is a considerable challenge for hotels. On average, one guest at most hotels creates about 0.9 kg of waste per day (Abdulredha et al., 2018). Aggregating it to a total number of hotels and guests worldwide, this is a significant amount. Study shows that for a hotel chain with 170 properties, reducing the food waste can save $4.7 million and reduce 1,160 tons of carbon emissions (Güçer & Özdemir, 2018). However, managing the waste at the sources may be impossible within the externalities involved with the sourced materials, availability, and human behavior (Rahman, Reynolds, & Svaren, 2012). This study focuses on using a smart sustainability performance measurement system (SPMS), which has gained acceptance as a powerful waste management tool (Fatimah, Govindan, Murniningsih, & Setiawan, 2020).

It is necessary to have a performance measurement system to monitor the sustainability management process to understand the situations and respond accordingly (He, Chen, Liu, & Guo, 2017). As a type of information system, smart SPMS facilitates the planning, implementation, and measurement of waste management processes through process automation, recording tracking, and data analysis (Buhalis & Leung, 2018). It allows hotels to monitor and measure sustainability performance in a smart manner. Like the environment, health, and safety management system, SPMS measures potential environmental, health, and safety impacts caused by production byproducts such as toxic waste. It also enables the measurement of broader environmental impact from energy uses such as electricity and water, recyclable materials, use of fertilizers, greenhouse gas emission, and so forth (Gössling, 2015). Thus, SPMS is a comprehensive approach that uses data and information to analyze and evaluate direct and indirect environmental impact resulting from various treatment options of waste. SPMS helps to understand the “big picture” of water, energy, and materials used during production and operations. The broad system perspective makes SPMS an effective system for environmental comparison of different options for waste management of a specific product, a material, or a complex waste flow (Cherubini, Bargigli, & Ulgiati, 2009; Ekvall, Assefa, Björklund, Eriksson, & Finnerveden, 2007). By tracking each activity and operational process with quantitative data, managers can determine how much excess is produced and then adjust planning for the future ordering of materials to prevent waste generation. Discussion around the role of technologies in hospitality has been a prominent theme in the smart tourism literature (Mehraliyev, Chan, Koseoglu, & Law, 2020). However, the role of SPMS in hotel sustainability management, especially in waste management, has not been discussed in prior studies. We identify this as one research gap in the smart tourism literature.

Prior research suggests that it is important to understand information systems as solutions for sustainability. For example, studies suggest that firms need management systems and tools...
that integrate environmental, health, and safety metrics with other process-related metrics to improve operational efficiency (Huang & Badurdeen, 2018). Prior research on information systems has made impressive strides in explicating whether and how information systems contribute to hotel performance at multiple levels (Piccoli, Lu, & Grün, 2017). However, sustainability management (e.g., waste management) needs a lifecycle approach focusing on the measure and tackling of the process. We could not find many studies that discuss information systems' role in such a context (i.e., SPMS in this study). Motivated by the gap in prior research and practice insights, the first research purpose of this study is to explore the impacts of SPMS on hotel ratings, reviews, and operational outcomes?

Some factors will cause different outcomes even when implementing SPMS. For example, these systems may not function effectively unless other resources, processes, and capabilities are in places, such as ownership management, functional and technical expertise, and reliable measurement of baseline indicators (Alfald, Kleindorfer, & de Miera Polvorinos, 2013). In such cases, the SPMS and organizational contexts and capabilities may prove inadequate or mismatched to produce positive effects. Given these realizations, examining the differences of SPMS on outcomes in different ownership contexts is a meaningful empirical question (Hodari, Turner, Sturman, & Nath, 2020). Following the prior studies, the first research purpose of this study is to explore the differences across different ownership types of hotels regarding the impact of SPMS on hotel ratings, reviews, and operational outcomes?

Overall, we argue hotels' customer ratings and reviews and hotel operational efficiency scores vary with SPMS implementations, influenced by some factors. Besides, the ownership type of a hotel may influence the value of SPMS implementations in the hotel. We analyze hotel data in the year 2016 from a large multinational hotel chain and matched hotel review and rating data from a well-known online tourism site. The findings suggest the value of SPMS on hotel performance. We also find that hotel ownership type can influence the value of SPMS. Research implications for emerging smart tourism literature, as well as managerial implications, are discussed.

2. Background and Theory

2.1 Information Systems and Waste Management in Hotels

Using IT for sustainability challenges, specifically to waste management activities, stems from the fact that various stakeholders such as customers, employees, and investors are demanding businesses to be sustainable (Jacobs, Singhal, & Subramanian, 2010; Khuntia, Saldamah, Mithas, & Sambamurthy, 2018). The increasing attention of academic research deals with sustainability considerations in various aspects of businesses, value chains, operations, and management (Atasu & Wassenhove, 2012; Joshi & Li, 2016). The context of IS in managing waste at the operational and process level in an organization is relevant and emerging as a central piece of discourse in the recent IT/IS enabled business research that should help in the energy consumption reduction (Khuntia et al., 2018) and carbon emissions monitoring (Melville, 2010). Organizations are increasingly looking for ways to manage IT-enabled sustainability practices (Atasu & Subramanian, 2012; Subramanian, Ferguson, & Beril Toktay, 2013). However, we know little about the relationship between IS and hotel performance (Melién-González & Bulchand-Gidumal, 2016). Also, how the effects of IS may differ at various other contingencies remains unexplored. This study fulfills these gaps in the literature exploring SPMS effectiveness on hotels' rating, review, and operational efficiency scores.

Sustainability management is a complex phenomenon with a range of consequences for the involved stakeholders and the society. The majority of the hotel corporations and individual hotel properties had implemented a program to measure their sustainability performance, including a waste management program (Franzoni, 2015). The practices implemented and the type of materials recycled varied by corporate's emphasis on the importance of recycling and the organization's infrastructure (Pirani & Arafat, 2014). There are many tools for assessing environmental impact, but one of the most commonly used is SPMS. The broad perspective of SPMS makes it possible to take into account the significant environmental benefits that can be obtained through different sustainability management processes (Searcy, 2012). For example, a study has shown how smart systems can be used for solid waste management, from information accumulation, waste generation prediction, decision support to evaluation and assessments, in European countries (Pires, Martinho, & Chang, 2011).

2.2 External and Internal Performance of Hotels

Reputation is a significant factor reflecting a business entity's performance, such as that of a hotel, especially for the online marketplace in recent years (Collier & Hampshire, 2010). The online reviews and ratings manifest a hotel's performance from its customers' perspective. For instance, an online review of a hotel reflects the hotel's reputation in the market space, and leads the hotel to achieve a benchmark in that reputational mechanism (Tadelis, 2016). Undoubtedly, this process is a signaling mechanism and a driver for customers' preferred choice for the hotel. Thus, hotels must have subsequent signal and choices work as a feedback loop to increase hotels' reputation. In the context of this study, they are maintaining a thread in the signal about sustainable behavior through sustainability management (Collier & Hampshire, 2010). Prior literature has shown that hotels tend to have better ratings and positive reviews if they have a good image regarding sustainability management (Bražytė, Weber, & Schaffner, 2017). By adopting SPMS, hotels can also provide a better environment and services to their customers (Peiró-Signes, Segarra-Olia, Verma, Mondéjar-Jiménez, & Vargas-Vargas, 2014). Prior studies have revealed the significant effects of word of mouth on a hotel's reputation and performance (Serra Cantallopols & Salvi, 2014; Sparks & Browning, 2011).

Besides external reviews and ratings, hotel performance can also be reflected through its internal operational efficiency regarding sustainability management (Barros, 2005). Traditionally, tourism industry activities' efficiency has received less attention, while it is critical for hotels to understand how to achieve the most effective operations (Sáez-Fernández, Jiménez-Hernández, & Ostos-Rey, 2020). Hotels implement sustainability management strategies to generate higher efficiency, leading to better economic and environmental outcomes. Studies have revealed that global hotel chains initiate their sustainability commitment to improving their lesser efficiency, including resource efficiency (Jones, Hillier, & Comfort, 2014; Zhang, Joglekar, & Verma, 2012). As part of the green business strategies, the implementation of environmental management systems and performance measurement systems were suggested to improve hotels' operational efficiency (Tooman, Sloan, Legrand, & Fendt, 2008). Following the suggested two perspectives of environmental sustainability management in hotels, this study also looks at the customer-centered and operations-centered hotel performance (Zhang et al., 2012).

2.3 Ownership of Hotels

Hotels can be managed by the hotel chain corporate or franchised by independent individuals. There are administrative or hierarchical techniques for the large hotel chain, such as creating standards or policies in the management (Cardinal, Kreutzer, & Miller, 2017). The type of ownership is reflected
through coordination mechanisms and budget appropriation in the organizational context or structure, including managerial techniques, decision-making, or task-directed leaderships (Birkinshaw, Holm, Thilenius, & Arvidsson, 2000). Thus, broadly two ways of management process: a directed and delegated task-activity process to the lower levels, or a process where the discretion is permeated to the lower levels through indirect channels than hierarchical delegation. The corporate-managed hotels would have a direct hierarchical structure and ownership control, while the franchised hotels would have more indirect control through different mechanisms.

We focus on the difference in approach to using SPMS across corporate-managed and franchised hotels. The corporate-managed hotels have a higher dependency on the corporate headquarters, relevant to resource allocations, overseeing activities, and adherence to a specific management approach (Birkinshaw et al., 2000; Songini & Gnan, 2015). In contrast, a franchise hotel may be independent in making decisions regarding the property while adhering to the hotel chain’s prevailing norms and guidelines. Corporate managed hotels have to align and follow the practices started and put in place by the headquarters. Denial to follow these approaches may lead the hotel’s headquarters to limit budget, resource, or benefit allocations (Songini & Gnan, 2015). A stringent oversight percolated to efficient implementation, follow-up, and management of SPMS and aligned other resources and capabilities to make the system succeed. Besides, frequently, with the implementation of a system, a corporate generally implements a set of performance measures to monitor and report marketable indicators (Pereira-Moliner et al., 2015).

3. Methodology

3.1 Data and Variable

The data for this study comes from a large multinational hotel chain. The hotel chain has several brands under its flagship and has different types of hotel ownership. The dataset comprises data of 3,969 properties for a single year in 2016. As part of the enterprise-wide program to adopt SPMS since 2009, the dataset reports sustainability management progress of corporate-managed and franchised properties. Among the 3,969 properties, 504 hotels have adopted the SPMS, and 3,421 hotels are in the U.S. In addition to the hotel chain data, we collected online ratings and reviews data of the hotels. The datasets are merged to conduct our data analysis. The descriptions of variables used in the data analysis are shown in Table 1. The descriptive statistics are presented in Table 2.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
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<tr>
<td>RATINGS</td>
<td>Average ratings of a property on a scale from 1 to 5</td>
</tr>
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<td>SCORES</td>
<td>The standardized score of a property’s operational efficiency on a scale from 1 to 5</td>
</tr>
<tr>
<td>REVIEWS</td>
<td>The number of reviews for a property. The total number of reviews was divided by 100.</td>
</tr>
<tr>
<td>SPMS</td>
<td>Whether a property adopted sustainability performance measurement systems to measure and report sustainability management, a positive value (e.g., 1) indicates a property has adopted SPMS.</td>
</tr>
<tr>
<td>MANAGED</td>
<td>Whether a corporate office manages a property, a property may be managed by a corporate or franchised to an independent owner. A property owner may choose to allow the corporate office to manage all of its operations. A positive value (e.g., 1) indicates a corporate office manages a property; otherwise, it is a franchised property.</td>
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Table 2. Descriptive statistics

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<td>1.47</td>
<td>0.95</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>REVIEWS</td>
<td>3,969</td>
<td>10.89</td>
<td>12.38</td>
<td>0.02</td>
<td>160.05</td>
</tr>
<tr>
<td>SPMS</td>
<td>3,969</td>
<td>0.13</td>
<td>0.33</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>MANAGED</td>
<td>3,969</td>
<td>0.17</td>
<td>0.37</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

3.2 Data Analysis

First, we conducted a t-test to evaluate the hotel performance between hotels that adopted the SPMS and hotels with no SPMS from three perspectives: customer ratings, operational efficiency scores, and customer reviews. Second, for hotels that adopted SPMS, we conduct a t-test to compare the differences between franchised and corporate-managed hotels. Besides, we offer visualizations of the data analyses.

4. Results

For the evaluations on SPMS usage value, Figures 1, 2, and 3 and Table 3 present the results. First, Figure 1 shows the customer ratings of hotels that use SPMS and have no SPMS. Both groups’ ratings have a very similar pattern, while the non-SPMS group has a slightly better rating performance. Second, Figure 2 shows the comparison of operational efficiency scores between the SPMS and non-SPMS groups. The scores are higher for hotels in the SPMS group, while for most hotels in the non-SPMS group, their scores are lower.
Table 3. Hotel performance by SPMS usage

<table>
<thead>
<tr>
<th>SPMS</th>
<th>Non-SPMS</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratings</td>
<td>4.33 ± 0.47</td>
<td>4.36 ± 0.44</td>
</tr>
<tr>
<td>Scores</td>
<td>2.12 ± 1.29</td>
<td>1.37 ± 0.85</td>
</tr>
<tr>
<td>Reviews</td>
<td>15.5 ± 16.0</td>
<td>10.0 ± 11.4</td>
</tr>
</tbody>
</table>

Results: compared to hotels with no SPMS, hotels that adopted SPMS have better operational efficiency scores and more reviews. There are slight differences between hotels with and without SPMS regarding the ratings.

Third, Figure 3 shows the customer reviews in hotels with and without SPMS. It is obvious that hotels with SPMS are more popular with more reviews than hotels with no SPMS. Table 3 summarized the t-test results regarding these three factors: ratings, scores, and reviews in the two groups: SPMS and non-SPMS. First, for the ratings, the t-value is 1.67, indicating slight differences between the two groups. Second, for the scores, the t-value is -17.07, suggesting that hotels with no SPMS, hotels that adopted SPMS have much better operational efficiency scores. Third, for the reviews, the t-value is -9.91. This result implies that hotels that have SPMS have more reviews.

Next, to examine the influence of hotel ownership type for hotels that adopt SPMS, Figures 4, 5, and 6 and Table 4 display the results. First, Figure 4 shows the customer ratings of hotels that use SPMS by hotel ownership types. For the majority of franchised hotels that adopted SPMS, their ratings are at a higher level. Second, Figure 5 shows the comparison of operational efficiency scores by hotel ownership type. The corporate-managed hotels outperform the franchised hotel regarding the scores. Third, Figure 6 shows the customer reviews in corporate-managed and franchised hotels. Corporate-managed hotels have more reviews than franchised hotels. Table 4 summarized the t-test results for ratings, scores, and reviews in the corporate-managed and franchised hotels. First, for the ratings, the t-value is 3.01. This result indicates that franchised hotels have better ratings when they adopt SPMS. Second, for the scores, the t-value is -4.21, implying that compared to franchised hotels, corporate-managed hotels that adopt SPMS have much better operational efficiency scores. Third, for the reviews, the t-value is -6.18, suggesting that corporate-managed hotels have SPMS have more reviews than non-SPMS ones.

Table 4. Hotel performance by hotel ownership type

<table>
<thead>
<tr>
<th>For Hotels That Adopt SPMS</th>
<th>Managed</th>
<th>Franchised</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratings</td>
<td>4.26 ± 0.47</td>
<td>4.38 ± 0.46</td>
<td>3.01***</td>
</tr>
<tr>
<td>Scores</td>
<td>2.38 ± 1.28</td>
<td>1.91 ± 1.25</td>
<td>-4.21***</td>
</tr>
<tr>
<td>Reviews</td>
<td>20.2 ± 18.9</td>
<td>11.8 ± 12.1</td>
<td>-6.18***</td>
</tr>
</tbody>
</table>

Result: When adopting SPMS, compared to hotels that are franchised, hotels that are managed by the corporate have much better operational efficiency scores and the number of reviews, while the franchised hotels have better ratings.
5. Discussion

Sustainability management is a complex activity for organizations, including hotels. Using information systems, hotels can efficiently improve their sustainability management (e.g., waste management) to reduce cost and carbon emissions. This study explores how SPMS may create value to improve hotel performance from the external customer perspective and internal operational efficiency perspective. The findings of this study provide interesting insights. We find that the usage of SPMS can improve a hotel's operational efficiency scores and increase the hotel's popularity with more customer reviews. These findings highlight the importance of adopting smart systems by hotels to improve their outcomes.

Furthermore, we studied whether there are differences across different types of hotel ownership. This study suggests that when adopting SPMS, franchised hotels have better customer ratings, while corporate-managed hotels have better operational efficiency scores and more reviews. The management structure, the resource allocation, and the connection with the corporate can explain such differences. In other words, as suggested in prior literature, with the direct hierarchical structure, the corporate-managed hotels may not have the motivation to improve the rating of the property. However, they need to follow the headquarters' instructions to fully implement and use the SPMS, increasing their operational efficiency and popularity among customers (Pereira-Moliner et al., 2015; Songini & Gnan, 2015). With corporate support (both financial and technical), the corporate-owned hotels can leverage the SPMS better than franchised hotels.

Previous literature has indicated the value of information systems for sustainability in a general context (e.g., Khuntia et al., 2018). Fewer studies have discussed information systems’ role in the hotel industry (Melián-González & Bulchand-Gidumal, 2016). The findings of this study are consistent with previous literature that highlighted the significance of information systems while providing findings in the context of hotel performance. This study also addresses the research gap by showing the differences across different ownership types of hotels. Given this study's findings, it is apparent that ownership is important when it comes to leveraging smart sustainability systems. Future research may explore salient factors associated with these ownership issues and may implicate deeper insights. In that regard, this study informs research to take a holistic perspective to smart systems implementations.

This study also has practical implications. First, hotels can adopt SPMS not only for their sustainability management but also for performance improvement. Armed with IT, hotels can gain both environmental and economic benefits. Second, for the large hotel chains, they can adjust their management strategy to ensure both franchised hotels and corporate-managed hotels achieve good performance, which is beneficial for the hotel brand.

There are some limitations of this study. This study is an initial explorative study that analyzes the variations across several key variables. The theoretical contributions are limited for this explorative study. Future studies can draw hypotheses and test causal models with more robust data and analytical approaches to inform further insights into the context of smart sustainability systems implementations.

Declaration of competing interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Tourist Transition Model among Tourist Attractions based on GPS Trajectory

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Abstract

Before COVID-19, tourist destinations have experienced problems with congestion of both famous tourist attractions and public transportation. Over-tourism is not an issue at this time, but it is likely to rekindle after the COVID-19 pandemic ends. One method of mitigating over-tourism is to estimate tourist behavior using a tourist transition model and consequently adjust public transportation operations. In this study, we propose a construction method for a model of tourist transitions among tourist attractions based on tourist GPS trajectory data. We construct tourist transition models using actual trajectory data for tourists staying in the vicinity of Kyoto City. The results verify the model performance.

Keywords

GPS; tourism informatics; tourist behavior modelling; over tourism; smart tourism

1. Introduction

Before COVID-19, over-tourism, i.e., extreme concentrations of tourists at famous tourist attractions and associated congestion of public transportation, has become a significant problem for many tourist destinations. Because of the pandemic, there are very few tourists in any tourist destinations, but the over-tourism problem is expected to rekindle after the COVID-19 pandemic. One way to avoid over-tourism is to reduce the number of tourists to the destination itself. For example, restricting the number of visitors during peak seasons or limiting the number of hotel licenses. However, these methods reduce the number of tourists and thus have a negative impact on the performance of existing tourism industry. Therefore, instead of restricting the number of visitors to the destination area, a method to reduce congestion by dispersing tourists to some tourism attractions within the destination has been required. For example, a method to avoid congestion by simulating where and when many tourists are likely to gather and informing tourists about it (Yang, Na, Li, Li, & Zhong, 2018), a method to disperse tourists by recommending personalized routes (Konstan et al., 1997; Zach & Gretzel, 2011). In order to realize or improve the accuracy of the above methods, tourist transition models between sightseeing attractions are effective, but until now, not much research has been done on the transition model. Especially, there is little research on tourists who travel mainly on foot. This is where the research gap lies.

We also need to think about what information to use to build models. To construct a tourist transition model among tourist attractions, information on the attraction locations is necessary. Some existing methods use external data such as tourist guidebooks and Wikipedia to obtain the information required for model construction (Horvitz & Krumm, 2012; Ziebart, Maas, Dey, & Bagnell, 2008). However, there are two disadvantages of collecting location information of tourist attractions from an external data source. First, with that external source approach is applied, only known tourist attractions can be reflected in the behavior model. Furthermore, there are many tourist attractions that are not well known and that do not appear in tourist guidebooks and on Wikipedia (Ieiri, Nakajima, & Hishiyama, 2018). Secondly, the time and effort required to collect such external data from multiple information sources, format the data, and input it into the system is a burden for users. The burden is especially heavy for small-size Destination Management Organizations (DMOs), which have fewer staff. On the other hand, there is a method of extracting tourist spots and building a model using only movement trajectories without using external information. If we do not rely on external information, the above disadvantages will not occur. In addition, it is a highly versatile method that can be used in any region, which is a great advantage. Therefore, a model representing transitions between tourist attractions that is not dependent on external data but, instead, depends on actual data reflecting all visited tourist attractions (e.g., global positioning system (GPS) trajectories) is required. From the informatics view point, it is challenge to make tourist transition model only from tourist behavior data without any other external data. From the practical view point, it is useful for DMOs because they should not collect any external data but GPS data.

In this study, we use GPS trajectory data to construct a tourist transition model; these data are employed because they can be collected automatically (with advance permission for privacy data usage from users) by having tourists carry GPS equipment such as smartphones. To extract tourist attractions from GPS trajectories, we focus on the tourist movement speed, because tourists tend to move slowly when sightseeing. However,
they also move slowly at stations or bus stops, when waiting for trains or buses. Thus, we first extract concentration points, which are points where tourists move slowly and include both tourist attractions and transit hubs. We then classify these points using the tourist speed distributions. Finally, we calculate the transition probability between tourist attractions. This is the proposed transition model.

The remainder of this paper is organized as follows. Section 2 discusses related works. Section 3 presents the proposed method, with subsections describing the extraction of tourist attraction data from GPS trajectories only and the construction of the tourist transition model. Section 4 reports construction of a tourist transition model based on actual data and its performance evaluation. Section 5 discusses and concludes this paper. This includes the scope, the limitation of our method, and outlines our future work.

2. Related Work

In this section, we describe the position of our study in the past researches on solutions against over- and furthermore, from the viewpoint of informatics, we describe the existing studies on the proposed method of tourist spot extraction and tourist behavior models.

2.1 Over-Tourism Management

Before the COVID-19 pandemic, over-tourism appeared like a sudden disaster, sweeping famous tourist destinations around the world. The studies for definitions or analysis of its causes are outside the scope of this study and will not be dealt with in this paper. In this paper, we will discuss the solution of over-tourism. In order to solve the problem of over-tourism, research has been conducted in the fields of business administration, transportation engineering, economics and informatics (Dodds & Butler, 2019). Based on these studies, main strategies are classified as follows: taxation, advance booking systems, creation of alternative routes, virtual access, limited number of hotel beds, restricted access to tourist attractions, leveling of the congestion, etc. (Krizaj, Brodnik, & Bukovec, 2014).

The authors believe that the proposed method is a technology to realize the strategies of creation of alternative routes and leveling of the congestion. One of the technologies to realize the alternative routes strategy is the route recommendation technology, which creates and proposes an efficient route around multiple spots (Konstan et al., 1997; Zach & Gretzel, 2011). In the past, most of the research in this field has been aimed at finding the shortest route in terms of distance and time, but in recent years, research has also been conducted to find a route that takes into account tourists' preferences and time constraints (Kurata & Hara, 2013; Quercia, Schifanella, & Aiello, 2014). Route planning methods that predict and take into account congestion have been proposed, but they are for cars and not for tourists, who are mainly on foot (Kuryayama, Murata, Shibata, Yasumoto, & Ito, 2007).

2.2 Extraction of Tourist Attractions

One of the purposes of this study is to find tourist attractions from tourist behaviors. This research topic can be regarded as a branch of the well-explored research domain that seeks to identify characteristic places by considering human behavior (Crandall, Backstrom, Huttenlocher, & Kleinberg, 2009; Kurashima, Iwata, Irie, & Fujimura, 2010). Studies detecting commonly used routes and traffic flows are also included in this research domain (Gonzalez, Hidalgo, & Barabasi, 2008; Omer & Jiang, 2015).

As a large number of behavioral records are required to find characteristic places, research is widely conducted using information posted by users of social networking services (SNSs) such as Twitter, Foursquare, Flickr, and Facebook (Ajao, Hong, & Liu, 2015; Pat, Kanza, & Naaman, 2015). Ajao et al. (2015) have defined seven types of Twitter spatial indicators: location mentions in tweet texts, friend networks, location fields, IP addresses, geotags, URL links, and time zones. Text mining of location mentions is broadly used by existing methods that identify characteristic places on SNS (Cheng, Caverlee, & Lee, 2010; Iwawa, Enoki, & Tatsubori, 2012; Maeda, Tsubouchi, & Toriumi, 2017; Schulz, Hadjakos, Paulheim, Nachtwy, & Mühlhäuser, 2013). Among them, geotags attached to photographs (Crandall et al., 2009; Dang-Quy, Piras, Giacinto, Boato, & Natale, 2017; Kurashima et al., 2010) or text (Han, Ren, Du, & Gui, 2020; Peng & Huang, 2017; Zheng, Li, Zha, & Chua, 2011) are generally used for detection of tourist attractions. Other location detection methods involving GPS trajectories, which are collected via mobile devices such as smartphones, are also used (Lv, Qiao, Ansari, Liu, & Yang, 2016; Massimo & Ricci, 2019; Okada et al., 2008; Palma, Bogorny, Kuipers, & Alvaras, 2008; Suhara, Toda, Nishikawa, & Washizaki, 2013; Zheng, Zhang, Xie, & Ma, 2009).

Crandall et al. (2009) and Kurashima et al. (2010) have proposed methods of extracting tourist attractions from pictures geotagged on SNS. Those methods operate under the assumption that tourists take many pictures of attractions, and cluster geotagged pictures to identify those attractions. However, the methods proposed by Crandall et al. (2009) and Kurashima et al. (2010) fail to distinguish between tourist attractions and transit points if applied to GPS trajectories. Therefore, we must classify tourist attractions and transit hubs to construct a model involving only tourist attractions.

Finally, Okada et al. (2008) presented a method of extracting tourist attractions from GPS trajectories that uses rest points identified according to movement speed. Tourists tend to decrease their movement speeds in the vicinity of a tourist attraction as the observe the sights, take photographs, and talk with companions. However, tourists also exhibit decreased movement speeds at other locations. Therefore, this method fails to classify tourist attractions and other points such as transit hubs.

2.3 Transition Model Construction

There are two topics regarding tourist transition model constructing: how to represent the transition of tourists and the use of external data.

As to how to represent the transition, existing studies on tourist-attraction transition models can be broadly divided into two categories, those considering grid models (Krumm & Horvitz, 2006; Takimoto et al., 2017; Xue et al., 2013, 2015) and those employing spot models (Ashbrook & Starner, 2003; Tamura, Kasahara, & Hibiki, 2014; Zheng et al., 2011). The former model accurately represents the geographical location, and the latter model abstractly represents the relationship between spots.

A grid model divides a geographical space of the target destination area into the same size cells. It is then assumed that the tourists move on those grids. Existing studies include those by Xue et al. (2013, 2015) and Krumm and Horvitz (2006). Since this model describes the transitions of tourists as a cell array, it can accurately represent the movement in geographic space. The problem with this model is that the size of the cells must be set relatively large in order to achieve sufficient transition probability when the cell size is small. In the approach developed by Xue et al. (2013, 2015), the destination prediction accuracy is highest when the cell side is 2 km. Krumm and Horvitz (2006) set the cell side to 1 km. However, for cell

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1 This paper is an extended version of the conference article “Tourist Transition Model based on Trajectory Data and Sightseeing Spot Detection” presented at the 26th Annual ENTER eTourism Conference in Nicosia, Cyprus.
sizes of 1 or 2 km, some tourist attractions may fall within the same cell. Additionally, in actual use, since it is necessary to adjust the optimum cell size for each tourist destination, there is a problem in practicality.

To establish a spot model, it is assumed that a tourist moves directly between tourist attractions. Related studies include those by Ashbook and Starner (2003), Zheng et al. (2011), and Tamura et al. (2014). In those methods, Markov models are employed and the geographical distance, transport networks, and data sparseness are neglected; however, it is difficult to determine the transition probability for a tourist attraction with few tourists.

Next, we describe the related works of the usage of external data for model constructing. In related works on tourist-attraction transition models, methods that try model improvement by using some external data have been used. Those methods employ GPS trajectories as well as external data such as polygon data on tourist attractions and route information. For example, Horvitz and Krumm (2012) predicted destinations using intersection location information, while Ziebart et al. (2008) used accident reports, road conditions, and driving habits. However, the external information used by those methods must often be renewed within a short period of time because of tourist attraction transitions. It is difficult to obtain all required information, such as tourist attraction changes, in advance.

### 3. Tourist Attractions Extraction and Model Construction

#### 3.1 Method Overview

Here, we present an overview of the method proposed in this paper. Our method consists of two parts; extraction of tourist attractions and construction of tourist transition model.

As noted above, tourist movement speeds tend to be low at attractions, because the tourists observe the sights, take photographs, and talk with companions. In the method proposed in this study, we first extract points with low movement speed from the tourist trajectory dataset; we call those points "rest points." We obtain the tourist concentration points by clustering the rest points. Next, we classify the tourist concentration points as either "tourist attractions" or "transit hubs," which are defined as points targeted and not targeted by tourists, respectively.

The network including all tourist concentration points is called the "concentration point network." We determine the transition probability between all concentration points from the concentration network. Using this probability, we build a tourist transition network consisting of tourist attractions only and obtain the tourist transition model.

#### 3.2 Extraction of Tourist Attractions

This subsection describes the method used to remove the trajectory measurement error and to extract the tourist attractions from the trajectories. As noted above, tourist movement speeds tend to decrease around our is attraction. However, as tourists may stop to wait for transportation (e.g., to take buses or trains), eat, and shop at locations other than tourist attractions, we must classify the concentration points into two categories. Tourists tend to move on foot around tourist attractions and to use other forms in transport in the vicinity of transit hubs. Therefore, those features were used to classify the concentration points into tourist attractions and transit hubs, as detailed in this subsection.

##### 3.2.1 Trajectory Preprocessing

In this work, a trajectory is a sequence of points, each with latitude (lat), longitude (lon), time stamp (t), and ID (id), as recorded by GPS equipment. GPS trajectories are automatically collected by GPS equipment such as smartphones with advance permission of user’s privacy data usage.

However, we must remove the GPS measurement errors from the trajectories. A trajectory featuring large errors is expected to have sudden speed changes. That is, tourist speed depends on transportation, but measurement errors cause larger speed changes than any transportation. Therefore, we add the velocity v to trajectory points obtained from the corresponding latitude and longitude values and classify the points where v is larger than the threshold $\nu_1$ as errors. These errors are then removed.

#### 3.2.2 Concentration Point Extraction

This subsection describes the method used to extract the concentration points from preprocessed trajectories. The concentration points are the tourist attractions and transit hubs.

There are two patterns through which tourists decrease their speeds for long periods of time, i.e., for sightseeing and for transfer. We extract the former as rest points. Temporary resting is shorter than that for sightseeing and transfer. In this work, we define $t_3$ as the longest time period of temporary resting and $v_3$ as the maximum speed for sightseeing and transit. When $v$ is continuously less than $v_3$ for more than $t_3$, we extract the intermediary points as rest points. These thresholds are empirically determined in this study.

Next, we obtain the tourist concentration points by clustering the rest points using the mean-shift method. We define the tourist concentration points $c$ as the centers of gravity of each cluster.

##### 3.2.3 Concentration Point Classification

In this subsection, we describe the method used to classify concentration points into tourist attractions and transit hubs. Tourists tend to move on foot at tourist attractions and in vehicles around transit hubs because they transfer to buses or trains. We classify the concentration points using these features.

First, we define the concentration point area $S$ as the area divided using Voronoi division. We define $I_{\text{walk}}$ and $I_{\text{trans}}$ as the areas in S a tourist can enter on foot and in a vehicle, respectively, with $I_{\text{lat}}$ being the union of $I_{\text{walk}}$ and $I_{\text{trans}}$ (Figure 1). We assume that the ratio of the area occupied by $I_{\text{trans}}$ in $I_{\text{lat}}$ is small and large for a tourist attraction and transit hub, respectively. We classify the concentration points using this assumption.

To obtain the area of $I_{\text{walk}}$ and $I_{\text{trans}}$, we create images of them using tourist speed data. First, we assume that points in the trajectory are "walking" and "riding points" if the speeds are lower and higher than $v_3$, respectively. Next, we create heat map images of the walking and riding points, and binary image from the heat map images for every concentration point. We call these binary images $I_{\text{walk}}$ and $I_{\text{trans}}$. Finally, we define the feature value $R_c$ as

$$R_c = \frac{M(I_{\text{trans}})}{M(I_{\text{all}})}$$

where $M(l)$ is the number of pixels in I and $I_{\text{all}}$ is the union of $I_{\text{walk}}$ and $I_{\text{trans}}$. If $R_c$ is smaller or larger than $R_0$, the concentration point is a tourist attraction or transit hub, respectively. In this study, $R_0$ is empirically determined.
3.3 Construction of Tourist Transition Model

In this subsection, we define the concentration point network and discuss construction of the tourist transition network and model.

First, we construct the concentration point network, which is a directed weighted network. It has concentration points as nodes. Edges exist if the transitions between the concentration points are along trajectories. The edge weight $p_{i,j}$ is the ratio of the transition from tourist concentration point $i$ to tourist concentration point $j$. We define $p_{i,j}$ as the probability of direct transition from node $i$ to node $j$.

Next, we construct the tourist transition network. Tourists do not use the shortest path only. Therefore, we define the probability of transition from node $i$ to node $j$, $p_{i \rightarrow j}$ as:

$$
P_{i \rightarrow j} = \frac{\sum_{r=d_{ij}}^{l_{ij}} M^r}{l_{ij}}
$$

where $M = (p_{i,j})$, $d_{ij}$ is the number of nodes on the shortest path from node $i$ to node $j$, and $l_{ij}$ is the upper limit of the number of nodes that can be traversed from node $i$ to node $j$. In this study, we define $l_{ij}$ as:

$$
l_{ij} = 2 \times d_{ij}
$$

Furthermore, $\alpha$ is a normalization term, with

$$
\alpha = \frac{1}{\sum_{c \in K} p_{i \rightarrow c}}
$$

Here, $K$ is the set of tourist attractions. We define the tourist transition network as a network that has tourist attractions as nodes and directed weighted edges as $p_{i \rightarrow j}$. In this work, we construct the tourist transition model using a Markov chain; that is, tourists’ subsequent destinations depend only on their current points.

4. Experiment

4.1 Preprocessing

Here, we report an experiment on a school trip excursion trajectory dataset for 579 students collected by Kasahara, Mori, Mukunoki, and Minoh (2015).

The trajectories were obtained by an application installed in a GPS unit, and were recorded in one-second intervals over a single day in December 2015. The experiment area was set to latitude 34.90 degrees or more, 35.15 degrees or less, longitude 135.65 degrees or more, 135.85 degrees or less. This area was selected to span Kyoto City, which was visited by a large number of students for a school excursion. The threshold value to eliminate outliers $v$ was set to 180 (km/h). As points measured using Assisted GPS and Wi-Fi have low accuracy, they were eliminated. The experiment dataset included 9,530,489 observation points, which was reduced to 5,108,676 observation points upon outlier deletion.

4.2 Concentration Point Classification

In this experiment, we used $v_s = 3.6$ (km/h) and $t_s = 200$ (s) for rest-point extraction. We also set the Gaussian kernel of the mean-shift method to 0.0010.

Using our method, we extracted 354 concentration points. Then, to evaluate the method performance, we classified them by hand, obtaining 170, 171, and 13 tourist attractions, transit hubs, and erroneous extractions, respectively. Figures 2 and 3 show the $R_c$ distribution of the proposed method and the receiver operating characteristic (ROC) curve, respectively. From Figure 2, the tourist attraction $R_c$ values are mostly smaller than 0.4187, whereas those of the transit hubs are mostly larger than 0.4187. Therefore, we used 0.4187 as the threshold $R_c$ in the model construction. The correct answer rate was found to be 76.6%.

Fig. 2. Distribution of threshold $R_c$

Fig. 3. ROC curve
Concentration points

Fig. 4. Correct classification (Ginkaku-ji Temple), \( R_c = 0.040 \)

Roads in Ginkaku-ji, \( L_{gt} \)

Examples of correct classification by the proposed method are shown in Figures 4 and 5. Figure 4 shows binary images created at the Ginkakuji tourist attraction, which is a famous temple in Japan. The \( R_c \) of this tourist attraction is very small, at 0.040. The figure shows that the roads inside Ginkakuji were extracted as \( L_{gt} \). Furthermore, it is apparent from the \( I_{trans} \) result on the left of the figure that the area has almost no car access. However, car access is indicated for small areas; this result was obtained because the speeds for the indicated points could not be measured correctly because of GPS measurement errors.

Figure 5 shows binary images created at the Yamashina Station transit hub. The \( R_c \) of this transit hub is very large, at 0.855. In the figure on the left (\( I_{trans} \)), the tracks were extracted as an area accessible by train. Furthermore, the \( L_{all} \) result (right) almost covers that for \( I_{trans} \).

Incorrect classification (Tofukuji Temple), \( R_c = 0.626 \)

An example of incorrect classification by the proposed method is shown in Figure 6, which presents binary images created for the Tofukuji Temple tourist attraction. There is a road oriented in a western direction from Tofukuji Temple; therefore, the \( R_c \) of this tourist attraction is very large, at 0.626. If a tourist attraction does not have another concentration point like this, the divided area can be so large that it contains additional features unrelated to the tourist attraction, as for the road and track visible in this case. Therefore, the \( R_c \) of this tourist attraction is large and misclassified.
4.3 Construction of Tourist Transition Model

To evaluate our model construction method, we constructed a tourist transition model for the experiment dataset. As an example, Figure 7 is a map showing Kinkakuji, which is a famous Japanese temple, and 10 tourist attractions and transit hubs with high transition probability from Kinkakuji. To evaluate the whole model, we assigned the tourist attractions to several areas and obtained the transition probability between each area. The results are listed in Table 7. From Table 7, the highest transition probability is from Kinkakuji to Kinkakuji Shariden, i.e., the same area. This is followed by high transition probabilities to Kiyomizu Temple or Kyoto Station. In addition, transition probabilities tend to be high between geographically adjacent areas. These results show that tourists may transition to popular points such as Kyoto Station and Kiyomizu Temple regardless of distance, or move to neighboring tourist attractions.

![Map of tourist attractions](image)

**Fig. 7.** Potential attractions from Kinkakuji Temple and transition-probability table

5. Discussion and Conclusion

In this study, we extracted tourist concentration points from trajectories only and classified them into tourist attractions and transit hubs. Furthermore, we proposed a method for modeling the transitions between tourist attractions. Using this method, it is possible to construct a network considering the presence of transit hubs.

This method was developed as a versatile method that can construct a transition model based only on the trajectories of tourists, with one of our aims being to deal with over-tourism. It fulfills the existing research gap that Over-tourism is a complex problem, and the scope of this paper is to reduce the concentration of tourists in specific attractions within a destination, and to level out the situation as a whole. Specifically, it is assumed to be incorporated into technologies for predicting congestion, recommending tourist attractions to visit next, and recommending routes to avoid congestion. Therefore, it cannot be applied to methods for limiting the number of tourists in a destination as a whole. In addition, the data used in this study is the behavioral history of students on school excursions, and the means of transportation used by the students were mainly walking and public transportation (buses, subways, trains, and cabs), not electric scooters, which have been increasingly used in recent years. (In Japan, the use of electric scooters on public roads is prohibited by law as of 2021.) However, other researchers have developed methods for estimating the means of transportation, and by using such methods, it is possible to include other means of transportation.

Future improvements are planned, such as development of a method for automatically determining the feature value threshold ($R_0$), the bandwidth of the mean-shift method, and the routes tourists may choose on the concentration point network.

Declaration of competing interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Empirical Research Article

Smart Tourism Development in Small and Medium Cities: The Case of Macao

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Abstract
As a popular concept, smart tourism is widely used as a strategic tool to improve the competitiveness of world tourism destinations. Taking Macao as a case study, this research explores the relationship between government, academic research, and smart destination applications, with a view toward investigating the utilization of smart technology to achieve service innovation, effective communication with tourists, and enhance the travel experience. The study summarizes the current situation of smart tourism in Macao, finding that most of the smart services in Macao rely on users to obtain information spontaneously and do not achieve real interaction and service demand. Suggestions and advice for smart development are provided.

Keywords
Macao; smart tourism destinations; mobile applications; VR/AR applications; Big data platform

1. Introduction

Smart cities and smart tourism have been popular topics in recent years (Jasrotia & Gangotia, 2018). The goal of building a smart city is to improve the quality of life for residents, which requires improving the connections between people and systems, governments, and other public and private entities. Smart tourism is a branch of smart cities that aims to provide solutions to tourists’ travel-related needs (Khan, Woo, Nam, & Chattoth, 2017), improve travel experience, and enhance the competitiveness of destinations (Xiang, Tussyadiah, & Buhalis, 2015). Smart tourism is often used to promote specific political agendas and sell technical solutions, where it is frequently used in the context of open data initiatives or for rather trivial projects such as promoting free Wi-Fi or the development of mobile application (Gretzel, Sigala, Xiang, & Koo, 2015). Governments, such as the U.S., Mainland China, and South Korea, have been taking initiatives to build the requisite infrastructure and develop the necessary technologies to support smart tourism development (Ye, Ye, & Law, 2020). Shafiee, Rajabzadeh Ghatari, Hasanzadeh, and Jahanyan (2019) mentioned that destination managers, academicians, and policymakers are involved in the construction of smart tourism destinations. They proposed a framework for sustainable smart tourism destinations and stated that the smart tourism actions are influenced by context conditions (economy, technology, environment, and social cultural) and also request the support from government. In other word, as Figure 1 shows, government support, context conditions and the result of academic research are important determinants that guide and influence the implementation of smart tourism destinations.

At present, although a large number of papers have proposed the system and application in the field of smart tourism, the current literature has various limitations to provide guidance for the development of smart tourism destinations, such as the general lack of a strong theoretical background for research on smart tourism destinations and the absence of collecting a large number of tourist perspectives to determine the effectiveness of the application of smart systems are the main issues that need to be addressed in the literature. (Gretzel et al., 2015; Kontogianni & Alepis, 2020). Research on smart tourism destination development needs to be combined with theory to explore the characteristics of different destinations, and case studies can provide targeted analysis as well as referenceable cases for smart tourism destination development. Koo, Shin, Kim, and Chung (2013) targeted smart tourism development in Korea, overviewed how Korea Tourism Organization’s information technology operation manages each channel, website, social networks, applications and suggests and advices for smart tourism future directions are provided base on the research findings. After analyzing the development of smart tourism in Dubai, Khan et al. (2017) concluded the key features of smart tourism destinations include the digitization of systems, processes and services; establishing higher-level connections with tourists for communities, governments and other departments in the destination; providing local residents with a platform to participate in products/services; a higher level of data generation and use through integrated smart systems; thereby achieving better management of tourists’ experience. The application of destination smart tourism is the focus of most published studies. However, the context conditions of the destination, government guidelines and the research in smart tourism related to the destination are often ignored. It remains unknown whether the development of smart tourism will be affected by the weak theoretical foundation of research, government guidelines, and current development status.

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There is the aim of this paper is to provide a case study on the development of smart destinations—using Macao as the research target—to explore the relationship between government, academic research and smart destination development in action.

Fig 1. The relationship between government, academic research and smart development in action

2. Macao Tourism Industry

Macao has been a special administrative region (SAR) of the People's Republic of China since 1999, and this small city is perched on a peninsula of only 29 km² of land at the mouth of the Pearl River Delta (Greenwood & Dwyer, 2017). Macao's economic development is stable. In 2019, Macao's GDP was about US $53.86 billion, and its per capita GDP exceed US $86000. In 2020, despite coronavirus pneumonia, Macao's GDP was still amounted to US $23.7 billion. The tourism industry is a key contributor to Macao's economy, and it has created many employment opportunities for local residents. Macao welcomed 39.4 million visitors in 2019, an increase of 10 percent compared with 2018, when 35.8 million people visited the territory (MGT0, 2020). Greater China markets continue to be the top sources of inbound visitors to Macao (Pang, Law, & Fong, 2019).

Macao tourism industry faces many challenges due to the rapid growth of tourism. For example, the concentration of tourist attractions in Macao makes it easy to overload the tourist areas and traffic jams often occur during the peak season. Many studies have focused on the different issues facing the tourism industry in Macao and Agyeiwaah (2019) argued that the impact of tourism over-development risks should alert attention from the Macao tourism office. Luo, Lam, and Ye (2019) found that policies and regulations, economics, marketing, management, government attitudes, expertise and manpower, facilities and attractions, and infrastructure issues are the main obstacles to the sustainable development of entertainment tourism in Macao. Thus, Macao may need a more sustainable approach to tourism development that incudes being a smart destination. "Sharing" tourists share tourism products such as sharing transportation, AirB&B services which could be a solution to reduce damages from tourism over-development, thus the sharing economy may be another angle for future smart tourism development in Macao. Smart tourism destinations can also aim to use resources in smarter ways and improve quality of life sustainably, not only for residents, but also for tourists (Cimbaljević, Stankov, & Pavlušović, 2019). Thus, building successful smart destinations can help Macao solve the current problems in the tourism industry, demonstrating its unique characteristics while providing higher quality services to visitors and promoting their interest in repeat visiting.

3. Literature review

Smart tourism can be considered as a unique phase in the evolution of Information Communication Technologies (ICTs) in the tourism sector, where the physical and governance dimensions of the tourism industry have gradually merged with the digital domain, as a result that tourism information systems have achieved new levels of intelligence, and fundamental changes in the way tourism experiences are created, shared, and consumed (Gretzel et al., 2015). The development of smart tourism brings a richer tourism experience for tourists, demonstrates a more flexible market structure and offers more business opportunities for new facilities, business models, and market value. The sign of smart tourism is embodied in the combination of leveraging the information technologies and physical infrastructure, which is an integral part of smart city development, including policy, human capital, innovation and IT infrastructure, natural resources and environment (Gretzel et al., 2015; Khan et al., 2017).

Smart destinations utilize information platforms to transform user data into solutions relevant to specific needs and create personalized services for users (Koo, Shin, Gretzel, Hunter, & Chung, 2016), which also brings various challenges. These challenges are attached to the three phases in which visitors use smart services to assist them in their visits to destinations (Ardito, Cerchione, Del Vecchio, & Ragugese, 2019). In the pre-trip stage, destinations facing the challenges of its online reputation, which has direct impacts on the travel destination selections of its potential visitors. Tourists may post negative reviews online, and some information may be false misleading or motivated by bribery, or out of malice, or even due to an aversion to electronic technology (Weaver & Moyle, 2019). Due to the psychological impact of word-of-mouth behavior, consumers are reluctant to share negative reviews, which would inflate their scores. The false information is unfair to other tourists also has a negative impact on the tourism development of destinations. In the on-site stage, whether smart devices successfully play a supporting role during the trip can also affect the travel experience and satisfaction of tourists at the destination, especially when unexpected situations arise, such as tourists forgetting to charge their phones or losing them during the trip (Weaver & Moyle, 2019). Data privacy is also one of the challenges that are frequently mentioned, travelers were concerned about data privacy during their trips to different destinations (Buhalis & Amaranggana, 2013). For the use of smartphone apps usually ask for personal data, privacy concerns regarding personal security may prevent users from sharing their data, even as travelers habitually choose to decline data requests from suppliers (Ardito et al., 2019). This leads to many smart applications not being fully used, or even not being used. In the post-travel stage, value-added services such as labeling of checked luggage, mailing of souvenir products at the destination, and reimbursement of invoices are also among the challenges for smart destinations to increase tourist loyalty (Buhalis & Amaranggana, 2013). The key factor that determines the competitiveness of smart cities and smart tourism is the efficient use of information technology in destinations (Khan et al., 2017). The core of the development of smart destinations is the effective use of information technology to consolidate shared resources and ensure the sustainability of the destination (Lopez de Avila, 2015; Roberto, Presenza, & Del Chiappa, 2013).

The ingenious implementation of smart technologies in the three phases of the tourist journey (pre-, on-site and post-trip) can appropriately reduce the impact of tourism on the lives of local residents and at the same time enhance the tourist experience. Most high competitive smart tourism destinations equilibrate the basic structural factors of smart tourism development, leadership, innovation and human-supported social capital, as well as enabling factors including technology applications and ICTs (Boes, Buhalis, & Inversini, 2016). The combination of theory and practice is a key to the development of any
destination, and a detailed analysis of its current situation can potentially provide insights and recommendations for the future development of smart tourism. In order to contribute to the literature and practice by providing some insights gained from investigating a case on how smart destination can be developed by exploring three data sources – literature search, government periodical archived data, and descriptions of actual smart applications. This study attempts to use Macao as a case study. It explores Macao’s smart tourism from both academic and practical perspectives, firstly reviewing and summarizing the literature on hospitality and tourism in Macao, then collecting the Macao government’s policies on smart tourism development and reviewing the smart applications that have been conducted in Macao. The development of smart tourism in Macao is discussed from both theoretical and practical perspectives.

4. Methods

The data collection of this study is divided into three categories: 1) collect literature in the form of hospitality and tourism research publications related to Macao; 2) government guidance, represented by tourism-related plans released from official government press releases; and 3) current smart tourism applications adopted by official channels in Macao. Qualitative research is used to analyze and discuss the content of the three selected categories. The data was collected from January 8 to March 14, 2021.

4.1 Macao-related Hospitality and Tourism Research

To review hospitality and tourism, Web of Science (formerly ISI Web of Knowledge) was selected as the database for searching for research articles. Web of Science is today’s premier research platform for information in the sciences, social sciences, arts, and humanities. Its 10 database indexes include ISI Web Of Science - SCIE, ISI Current Contents Connect; ISI Proceedings; the Derwent Innovations Index; Biosis Previews; INSPEC; MEDLINE; ISI Journal Citation Reports; ISI Essential Science Indicators; and ISI HighlyCited.com (Clarivate analytic, 2019). An advanced search for articles published from 1995 and 2021 was conducted using the topic words “Macau OR Macao” under the hospitality leisure sport tourism category. A software-based scientometrics approach was adopted using a software application called CiteSpace to analyze the collected research articles. In early March 2021, 313 hospitality- and tourism-related research articles were found from Web of Science, dated from 1995 to 2021. Two analyses were selected: “Keywords with the Strongest Citation Bursts” and “Time-zone view of the keywords.” Only one study meeting these criteria in the tourism and hospitality area was published before 2006, which is Hobson’s (1995) study on the Macao gaming industry. Therefore, the analysis included studies from 2006 to 2021.

4.2 Government Policies

The details of Macao’s government policies related to smart tourism development was captured by consulting MGTO’s annual press releases. This study collected all the annual press releases that mentioned the use of ICTs and smart technologies to develop Macao’s tourism industry. Finally, data was collected from the years 2014 to 2021, from the official MGTO website.

4.3 Smart Tourism Applications

Macao smart tourism applications were mainly collected from google search engine, by searching “Macau/Macao smart tourism development” “Macao/Macau smart tourism applications” and “Macao/Macau smart phone applications” two sources are considered for collection. The first was the official announcements of Macao government departments. The second was to find popular smart applications that are promoted by the public in Macao such as news report or promotional ads. The definitions of these smart applications are obtained from the news, official webpage or the app download page. As the study was designed for smart destinations development, considering the validity and authenticity of the applications, this article only collects the smart applications provided and supported by the official, privately launched as well as the smart applications related to hotels and restaurants were not collected.

5. Findings

5.1 Macao-related Hospitality and Tourism Research

Table 1 displays a list of 25 keywords with the strongest citation bursts. Among the top 10 keywords, the terms “Service quality,” “Casino,” “Involvement,” “China,” “Destination image,” “Gambling,” “Tour guide,” “Quality,” “Destination,” and “Experience” were popular.

From the time series, the popular terms before 2014 are “Gaming,” “Casino,” “Issue,” “Tour guide,” “Place,” “China,” “Interpretation,” and “Quality.” This indicates that academic research on Macao before 2014 mainly focuses on the study of Macao’s gaming industry as well as solutions for the current problems of tourism development. For example, Gu and Siu (2009) examined the relationship between work performance and job satisfaction in Macao’s casino hotels. Hsu and Gu (2010) investigated Macao’s gaming boom and the planned construction of the Hong Kong, Macao and Zhuhai (HMZ) Bridge, which would present good opportunities for the three destinations to develop tourism. The transformation of Macao’s destination image refers to the views of tourists and its residents, since the image of casinos is still very important in the eyes of residents and tourists. Although MGTO is trying to downplay casinos, developing attractive broad-based tourism products has remained a challenge for a long time (Kong, du Cros, & Ong, 2015).

From 2015 to 2017, the keywords are “Expectation,” “Destination,” “Customer satisfaction,” “Service quality,” “Corporate image,” and “Destination image.” This shows that, since 2015, academic research on Macao has begun to focus on destination development (Vong, 2013); establishing destination image (Loi, So, Lo, & Fong, 2017); improving tourists’ satisfaction (Choi & Yoo, 2017); and service quality (Ji, Li, & Nie, 2017).

From 2017 to 2021, the keywords are “Behavioral intention,” “Involvement,” “Experience,” “Corporate Social Responsibility (CSR),” “Knowledge,” “Food,” “Intention,” “Co-creation,” “Identity,” and “Event.” These keywords involve a wide range of research, which shows that, after 2017, Macao tourism research topics are not limited to the gaming industry, destination development and tourists’ satisfaction. They have expanded to involve in various other aspects of the tourism industry. For example, Io and Chong (2020) attempted to empirically investigate Macao residents’ perception and enjoyment of Cantonese opera as a traditional performing art. Chan and James (2020) examined how hospitality employees’ experience of organizational politics, emotional exhaustion, job satisfaction, and turnover intention are linked.

From the time node of these keywords, Macao tourism research topics have become more abundant and profound. However, studies on the topic of the impact of ICTs on the development of tourism destinations are very few, and no influential keywords appear in Table 1. This implies that smart tourism or ICTs applications in the Macao tourism industry have not aroused attention from academia.
This indicates limited research on the application of smart tourism and ICTs in tourism. There was only one topic, in 2019, covering "social media." In fact, out of 313 published articles, only 14 studies focused on the impact of ICTs on Macao’s tourism industry, including mobile applications (Lai, 2015; Li, Su, Xu, & Yao, 2019); e-word-of-mouth (eWOM) and user generated content on social platforms (Lai, 2020; Vincent, 2018; Wang, 2015); information channels (Chen, 2019; Choi, Lehto, & Morrison, 2007; Choi, Tam, Kim, & Kim, 2018); and hotel websites (Chan, Wu, & Vipulakom, 2020). This indicates limited research exploring ICTs and the development of Macao’s tourism industry, and there is almost no research on Macao’s smart tourism.

### 5.2 Government Guidance in Smart Tourism Development

The gist of Macao government guidance related to smart tourism is given in Table 2, in chronological order, for the purpose of identifying smart tourism strategies that MGTO tries to deliver for tourism development. In 2014, MGTO started a marketing effort concentrating on developing online tourism promotions and enriching information about Macao on online platforms. 2015 marked the first time that MGTO announced the setup of a new tourist information counter at the new ferry terminal at Pac On in Taipa, to foster smart tourism development and electronic marketing.

In 2016 and 2017, MGTO continued to promote development of electronic administration and promote smart tourism as one of its major priorities. It utilized ICTs as promotion methods, including partnering with well-established online platforms and bloggers to further promote the destination on the Internet.

Since 2018, in addition to the development of smart tourism, MGTO began to establish a large tourism database for better cooperation with the tourism industry and to solve the problem of tourist carrying capacity problem in Macao. In 2019, the concept of big data was first mentioned by MGTO as it announced efforts to harness big data to analyze visitor behavior and provide grounds for studies on forming future destination marketing strategies and launching a newly designed Macao tourism promotion website.

In 2020, MGTO continued to develop its big data platform and share data on Macao tourism with the public. It also integrated the current content of its “Experience Macao,” “Step-Out, Macao” and “What’s On, Macao” mobile apps to provide a one-stop mobile application for Macao travel. Its tourism for 2021 is to open more tourism-related data via the Macao SAR Government Open Data Platform to unblock information isolation on the island while leveraging the tourism information interchange platform to compile tourism industry information and widen the potential of smart tourism development.

These findings show that Since 2014, MGTO has been performing a central role in the development of smart tourism in Macao. However, after years of efforts and promotion, the current situation of smart tourism development in Macao is still unclear. Very few studies have tried to analyze the application of ICTs or the development of smart tourism in Macao. The combination of theory and practice is the key to the development of the destination. A detailed analysis of the current situation of the destination will provide solutions for the future development of smart tourism.

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### Table 1. Top 25 keywords with the strongest citation bursts

<table>
<thead>
<tr>
<th>Keywords</th>
<th>Strength</th>
<th>Begin</th>
<th>End</th>
<th>2006 - 2021</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gambling</td>
<td>2.7217</td>
<td>2009</td>
<td>2012</td>
<td></td>
</tr>
<tr>
<td>Casino</td>
<td>3.425</td>
<td>2009</td>
<td>2014</td>
<td></td>
</tr>
<tr>
<td>Issue</td>
<td>2.9404</td>
<td>2009</td>
<td>2013</td>
<td></td>
</tr>
<tr>
<td>Tour guide</td>
<td>2.6049</td>
<td>2010</td>
<td>2013</td>
<td></td>
</tr>
<tr>
<td>Place</td>
<td>1.6459</td>
<td>2011</td>
<td>2013</td>
<td></td>
</tr>
<tr>
<td>China</td>
<td>3.1439</td>
<td>2011</td>
<td>2014</td>
<td></td>
</tr>
<tr>
<td>Interpretation</td>
<td>1.6459</td>
<td>2011</td>
<td>2013</td>
<td></td>
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<tr>
<td>Expectation</td>
<td>2.1978</td>
<td>2012</td>
<td>2015</td>
<td></td>
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<tr>
<td>Quality</td>
<td>2.3703</td>
<td>2012</td>
<td>2013</td>
<td></td>
</tr>
<tr>
<td>Destination</td>
<td>2.2266</td>
<td>2014</td>
<td>2016</td>
<td></td>
</tr>
<tr>
<td>Customer satisfaction</td>
<td>1.5449</td>
<td>2014</td>
<td>2017</td>
<td></td>
</tr>
<tr>
<td>Service quality</td>
<td>4.0442</td>
<td>2014</td>
<td>2017</td>
<td></td>
</tr>
<tr>
<td>Behavioral intention</td>
<td>1.9072</td>
<td>2015</td>
<td>2018</td>
<td></td>
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<tr>
<td>Corporate image</td>
<td>1.9976</td>
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<td>2017</td>
<td></td>
</tr>
<tr>
<td>Destination image</td>
<td>2.8582</td>
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<td>2017</td>
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<tr>
<td>Involvement</td>
<td>3.2112</td>
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<tr>
<td>Experience</td>
<td>2.2222</td>
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<td>CSR</td>
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<td>Knowledge</td>
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<td>Food</td>
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<td>Co-creation</td>
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<td>Identity</td>
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<td>2021</td>
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<tr>
<td>Event</td>
<td>1.7939</td>
<td>2019</td>
<td>2021</td>
<td></td>
</tr>
</tbody>
</table>
Table 2. Macao Government guidance related to smart tourism development

<table>
<thead>
<tr>
<th>Year</th>
<th>Details of Government Guidance Related Smart Tourism Development</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014</td>
<td>Concentrate on developing “Useful Tourism-Info e-Platform; design a mobile application for MGTO’s publication and reform its publication of “Macao Travel Talk” by enriching its online content.</td>
</tr>
<tr>
<td>2015</td>
<td>Foster smart tourism development and electronic marketing.</td>
</tr>
<tr>
<td>2016</td>
<td>Promote smart tourism as one of the major priorities among other strategies.</td>
</tr>
<tr>
<td>2017</td>
<td>Continue to develop smart tourism and leverage means of technology such as popular websites, mobile applications, social media platforms, and search engines to promote Macao.</td>
</tr>
<tr>
<td>2018</td>
<td>Boost smart tourism development by harnessing innovative technology to enrich the travel experience of visitors, building a large tourism database as well as reinforcing management of tourism carrying capacity.</td>
</tr>
<tr>
<td>2019</td>
<td>Conduct data collection and dissemination for the tourism information interchange platform and build a tourism big data database.</td>
</tr>
<tr>
<td>2020</td>
<td>Expand the scope of application of the tourism big data database to enable travel trades to share and harness the data; develop an intelligent itinerary planner to provide tailor-made travel routes for visitors with different interests.</td>
</tr>
<tr>
<td>2021</td>
<td>Open more tourism-related data via the Macao SAR Government Open Data Platform to unblock information isolation on the island, while leveraging the tourism information interchange platform to compile tourism industry information and widen the potential of smart tourism development.</td>
</tr>
</tbody>
</table>


5.3 Smart Applications in Macao Tourism Industry

Macao government issued the “Macao Smart City Development Strategy and Key Field Construction Consultation Text,” which clarified 13 key construction areas including infrastructure, big data, transportation, environmental protection, tourism, medical care, and education. At the same time, six projects including smart streetlights, Macao in the bag, government big data platform, smart city logo, smart city application and solution project funding, and municipal facilities EasyGo will be piloted in the early stage to create a people-oriented, sustainable smart city (Macao monthly, 2020). The Macao Government Tourism Office (MGTO) is cooperating with the Special Administrative Region government on its “smart city” development strategy and has launched many smart tourism projects into service (Travel PR News Editor, 2019). In 2019, MGTO officially launched three smart tourism projects into service (Travel PR News Editor, 2019), which fully capitalizing on the leading technology of Alibaba Cloud on cloud computing, big data application and other areas to push forward smart tourism.

Table 3 shows smart applications provided and supported by the official channels in Macao, with nineteen applications listed. These applications include mobile applications, virtual reality (VR), augmented reality (AR), QR codes, websites, and a tourism data exchange platform. Mobile applications are the most widely applied smart technology in the Macao tourism industry, followed by VR/AR/QR code technologies, and data exchange platforms. Most of the applications consist with the review result of Kontogianni and Alepis (2020), except the privacy preserving, context awareness and user experience. Fortunately, tourists visiting Macao have a very positive attitude towards using smart technologies (Pai, Liu, Kang, & Dai, 2020). It is important to increase the collaboration between public and private companies for the development of new or improved
ICTs-enabled tourism services towards the smart transformation of Macao (Errichiello & Marasco, 2017).

The listed applications are further categorized into five groups based on their function, these groups are defined based on the 6As from studies of Buhalis (2000) and Buhalis and Amaranggana (2013) to measure the success of a tourism destination, the 6As include Attractions; Accessibility; Amenities; Available Packages; Activities; and Ancillary Services. This study revised the 6As as following groups, attraction referring to the smart applications is utilized in attractions in Macao. Ancillary refers to smart applications that help tourists enhance their travel experience. Activity represents smart applications that facilitate activities that tourists may conduct in Macao. Transportation means smart applications that can be applied to transportation and navigating traffic in Macao, and Data Exchange Platforms are the online big data platforms that the Macao government is sharing with the public.

Ancillaries is the largest group and contains most of the applications, which implies that these applications more likely act as assistant tools to promote travel and help tourists search for information before and during their trips. Based on their functionality of these apps, they appear to be aimed at helping tourists in the pre-travel and on-site stages. This makes sense given that tourist behavior changes according to their travel experience and their travel phase. For example, at the pre-travel stage, they will seek more destination information for preparation and selection; during the on-site stage, they are more likely seeking destination facilities to assist their trip; and during the post-travel stage, they may share their travel experiences (Akhoondnejad, 2015). However, in Macao there is a lack of smart applications that address tourists’ post travel needs.

Table 3. Tourism related smart applications provide by official channels in Macao

<table>
<thead>
<tr>
<th>Name of the Applications</th>
<th>Smart Tech. Tools</th>
<th>Travel Phases</th>
<th>Description of Smart Experience</th>
<th>Government Departments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Macao Museum’s virtual tour</td>
<td>Mobile app</td>
<td>Pre-travel, On-site</td>
<td>A mobile app that has three functions comprising virtual reality (VR), augmented reality (AR), and QR code. Users can enjoy an immersive 720-degree panoramic view of the first, second and third floors of the Macao Museum and the Mount Fortress Garden with virtual reality (Macao Museum Macao Museum VR/AR, 2021).</td>
<td>Macao Museum</td>
</tr>
<tr>
<td>Macao Cultural and Creative Map</td>
<td>Mobile app</td>
<td>Pre-travel, On-site</td>
<td>A mobile app provides relevant data on Macao’s cultural and creative entities, with GPS and shop hunting functions for users’ easy browsing of cultural and creative spaces and quaint shops full of peculiarities (Macao Cultural and Creative Map, 2017).</td>
<td>Cultural Affairs Bureau of Macao</td>
</tr>
<tr>
<td>World Heritage (WH) Macao</td>
<td>Mobile app</td>
<td>Pre-travel, On-site, Post travel</td>
<td>A mobile app creates the effect of “strolling through the Historic Centre of Macao” by providing detailed descriptions of World Heritage sites; interesting multi-media information (short video clips, photographs, 360-degree views, activities related to the locale, etc.); and various interactive functions (a route guide linking the Heritage sites, Facebook functionality, etc.) (WH Macao, 2011).</td>
<td>Cultural Affairs Bureau of Macao</td>
</tr>
<tr>
<td>Step out</td>
<td>Mobile app</td>
<td>Pre-travel, On-site</td>
<td>A mobile app offers eight suggested walking tour routes in Macao (Step Out, 2020).</td>
<td>Macao government tourism office</td>
</tr>
<tr>
<td>Experience Macao</td>
<td>Mobile app</td>
<td>Pre-travel, On-site</td>
<td>A mobile app offers attraction information to tourists with multiple functions including: Information of Tourist Spots, Shows &amp; Entertainment, Accommodation, Restaurants, etc; 360-degree Panorama Photos; Audio Guide; Trip Planner; Offline Map; Augmented Reality (AR) function; and Game (Experience Macao, 2021). The Macao Post and Telecommunications Bureau (CTT) promotes different local organizations using the uniform network name “FreeWiFi.MO” to provide free Wi-Fi service to citizens and tourists (FreeWiFi.MO, 2018).</td>
<td>Macao government tourism office</td>
</tr>
<tr>
<td>Macao ready go</td>
<td>Online platform</td>
<td>Pre-travel, On site</td>
<td>An online platform introduces Macao’s promotional information including dining, accommodations, shopping, entertainment, local tours, and news (Macao ready go, 2021).</td>
<td>Macao government tourism office</td>
</tr>
<tr>
<td>What’s on Macao</td>
<td>Mobile app</td>
<td>Pre-travel, On site</td>
<td>A mobile app introduces Macao’s latest tourist attractions and monthly highlights from local events, activities, festivals, performances to exhibitions (What’s on Macao, 2019).</td>
<td>Macao government tourism office</td>
</tr>
<tr>
<td>MGTWeichat</td>
<td>Social media</td>
<td>Pre-travel, On site, Post travel</td>
<td>Official social media account established by MGT Macao to ease travelers’ travel experience (MGTWeichat, 2021)</td>
<td>Macao government tourism office</td>
</tr>
<tr>
<td>QR Code for Cultural and Creative Venues</td>
<td>QR codes need assistance from smart phone devices</td>
<td>Pre-travel, On site</td>
<td>The public can use this app to scan the QR code of “Works of Literature” with their mobile devices in order to link to the corresponding website (QR Code for Cultural and Creative Venues, 2015).</td>
<td>Cultural Affairs Bureau Macao</td>
</tr>
<tr>
<td>Macao Light Festival</td>
<td>Mobile app</td>
<td>Pre-travel, On-site</td>
<td>Macao Light Festival brings light installations, interactive games, and projection mapping shows accompanied by music. Visitors can participate in this festival by playing online games and downloading mobile apps (Macao Light Festival, 2019).</td>
<td>Macao government tourism office</td>
</tr>
<tr>
<td>Macao Grand Prix</td>
<td>Mobile app</td>
<td>Pre-travel, On-site</td>
<td>A mobile app named Macao GP supports detailed information on this auto racing event (Macao Grand Prix, 2021)</td>
<td>Sports Bureau of Macao</td>
</tr>
<tr>
<td>Macao Marathon</td>
<td>Mobile app</td>
<td>Pre-travel</td>
<td>The Macao Marathon mobile app provides race information to its attendants and fans (Macao Marathon, 2021).</td>
<td>Sports Bureau of Macao</td>
</tr>
</tbody>
</table>
6. Discussion

Research findings showed that there is a disconnect between research on smart tourism in Macao and the development of smart tourism by MGTO. Figure 3 illustrates the development of smart tourism in Macao under the influence of academia and government. This case study successfully demonstrates the different impacts of academia, government and practice on smart destinations. It confirms the common problems in the development of smart destinations, such as the lack of theoretical guidance and the over-reliance on smartphones for smart applications in destinations, most of which can only provide assistance to tourists before and during their visit, and the lack of value-added post-tour services for destinations. The detailed analysis of its findings contribute references and guidance for the current research on smart tourism destinations.

Apparently, smart tourism has become one of the important market strategies for tourism development that the Macao government has focused on since 2015, for example, promoting smart tourism, designing and increasing smart related tourism applications, establishing tourism big data database and opening up related data resources. To better promote the development of smart tourism in Macao, six government departments the Macao Museum, Cultural Affairs Bureau of Macao, Macao Post and Telecommunications Bureau, Sports Bureau of Macao, Transport Bureau of Macao and MGTO are actively involved in the creation of smart applications and have launched a number of smart applications to enhance the tourism experience. However, there is a dearth of research on smart tourism in Macao, with most of the research related to smart tourism focusing on eWOM, destination image and usefulness of interaction or service demand.

Therefore, the research on smart tourism in Macao should focus on the relevant smart applications launched by the government and assist government policies to integrate smart services to provide effective services to tourists.

Currently, multiple smart applications are widely promoted in the Macao tourism industry. This shows the contributions and efforts of government and enterprises to enhance the competitive strength of Macao as a tourism destination. MGTO put forward a proposal for the development of smart tourism destinations in 2015, and it has since committed to the extensive development of smart applications. These include multiple mobile applications to assist tourists before and during their trip; VR/AR/QR code apps to improve travel experiences at Macao heritage and cultural sites; a tourism data exchange platform; unlocking big data platforms for translation into smart tourism services such as data sharing and monitoring tourist flow; providing smart infrastructures such as intelligent transportation systems; and launching free Wi-Fi zones in multiple public areas.

Nevertheless, this does not mean that Macao is a successful smart tourism destination. Achieving smartness is not just simply using technologies to assist tourists in traveling. More importantly, smart technologies can be used to maintain sustainable development and display the uniqueness of a destination (Pai et al., 2020). However, Macao’s smart applications strive to integrate ICTs with physical infrastructure and penetrate the utility of these applications into different aspects of tourism. In fact, according to Gretzel, Ham, and Koo (2010)’s five layers of descriptions to illustrate smart tourism applications, these smart applications are applied to the first three layers: the physical layer; applied to natural and human-made touristic resources as well as transportation and service infrastructures; the smart technology layer that links to this physical infrastructure and provides back-end business solutions and front-end consumer applications; and the data later, where Macao’s has limited applications such as its open data platform. Thus far, Macao has not implemented applications in the business layer, which innovates based on available technologies and corresponding data sources, or the experience layer, which consumes generated technologies and enhances the experience of data. Most of the smart services in Macao rely on users to obtain information spontaneously and do not achieve real interaction or service demand.

<table>
<thead>
<tr>
<th>Data Exchange Platforms</th>
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<td>Smart visitor flow &amp;</td>
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<tr>
<td>application</td>
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<tr>
<td>Online data</td>
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<tr>
<td>platform</td>
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<tr>
<td>Pre-travel</td>
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<tr>
<td>A free access online</td>
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<tr>
<td>platform that predicts</td>
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<td>the density of visitor</td>
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<td>flow in tourist</td>
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<tr>
<td>attractions for a</td>
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<td>period of four hours,</td>
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<tr>
<td>24 hours and seven</td>
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<td>days. It issues ratings</td>
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<tr>
<td>that make it easier</td>
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<tr>
<td>to organize visitor</td>
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<tr>
<td>and tourism industry</td>
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<tr>
<td>operator itineraries</td>
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<tr>
<td>(Smart visitor flow</td>
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<tr>
<td>application, 2019).</td>
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<tr>
<td>Tourism data</td>
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<tr>
<td>exchange platform</td>
</tr>
<tr>
<td>Online data</td>
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<tr>
<td>exchange platform</td>
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<tr>
<td>Pre-travel</td>
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<td>On site</td>
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<td>The tourism data</td>
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<td>exchange platform is</td>
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<td>was created in the cloud</td>
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<td>computing network of</td>
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<td>the Government of Macao,</td>
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<td>to tourism in the</td>
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<td>territory (Tourism data</td>
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<td>exchange platform, 2019).</td>
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<tr>
<td>Visitor observation</td>
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<tr>
<td>application</td>
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<tr>
<td>Free access online</td>
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<tr>
<td>platform</td>
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<td>Pre-travel</td>
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<td>On site</td>
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<tr>
<td>Post travel</td>
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<td>A free access online</td>
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<td>platform that provides</td>
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<td>insights into the basic</td>
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<td>attributes and group</td>
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<td>behavior of visitors</td>
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<td>It is used to take a</td>
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<td>snapshot of the situation</td>
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<td>as well as the</td>
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<td>preferences and travel</td>
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<td>behavior of visitors</td>
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<td>to Macao (Visitor</td>
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<td>observation application,</td>
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<td>2021)</td>
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</tbody>
</table>

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<table>
<thead>
<tr>
<th>Transportation</th>
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<tbody>
<tr>
<td>DSAT-Traffic</td>
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<tr>
<td>Information</td>
</tr>
<tr>
<td>Station</td>
</tr>
<tr>
<td>LED variable</td>
</tr>
<tr>
<td>message signs</td>
</tr>
<tr>
<td>Mobile apps</td>
</tr>
<tr>
<td>On-site</td>
</tr>
<tr>
<td>A mobile and GPS platform for real-time bus transportation information (Bus Traveling System, 2021; Bus Stop for the Visually Impaired, 2021)</td>
</tr>
</tbody>
</table>

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In conclusion, the development of smart tourism in Macao is still in an early stage, and there is no systematic plan to provide a direction for the future development of Macao as a smart destination. Most smart apps rely heavily on smartphones as a medium and do not overcome the challenges that travelers encounter before, during, and after a trip. The development of smart tourism in Macau should focus on solving the problems of eWOM, protecting user privacy and value-added services in the post-trip stage. Combining academic research with government planning to provide theoretical support for smart tourism development can further develop Macao’s limited tourism resources and it can help demonstrate Macao’s tourism characteristics beyond the gaming industry.

7. Conclusion

This study has achieved its research objectives and discussed the relationship between government policies, smart applications, and academic research on the development of smart tourism by analyzing current smart tourism development in Macao. The study found that the destination government is very active in the development of smart tourism, and many smart applications are widely used in different aspects in tourism. However, these applications are fragmented and common technologies, and they cannot improve the uniqueness of destinations. It is also crucial to conduct academic research to verify the effectiveness of these applications in tourism services. The development of smart tourism destinations is necessary to combine theoretical support to analyze the characteristics of destinations and enlarge their advantages. Future smart tourism development should concentrate on the following key features: the digitization of systems, processes and services; establishing higher-level connections with tourists for communities, governments and other departments in the destination; providing local residents with a platform to participate in products/services; and creating a higher level of data generation to be used through integrated smart systems, thereby achieving better management of tourists’ experience (Khan et al., 2017). There is no survey of people involved in smart tourism, including tourists and government officers, which is one of the limitations of the present research. Future research may consider using quantitative or qualitative research to conduct in-depth research on relevant populations.

Declaration of competing interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.


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Empirical Research Article

The Use of Travel-Related WeChat Mini-Programs in China: An Affordance Theory Perspective

Ao Cheng, Chulmo Koo, and Hyejin Yoon

Abstract
The travel-related applications on a smartphone help tourists make a reservation before their trip conveniently; use a map, direction guidance, and translation services during the travel; evaluate and recommend travel services communicating with others after their journey. This study examines the relationships among affordances and constraints provided by the mini-program, users’ perceived value, and travel-related mini-program (TRMP) usage by analyzing the structural equation modeling. An online questionnaire was developed from the available scales in the published literature. A total of 651 TRMP users responded to the survey, and 448 valid responses were included for analysis. Affordance, including physical, cognitive, sensory, and functional affordance, significantly influenced the hedonic value of TRMP; utilitarian value except for cognitive affordance. There were negative relationships between unfamiliarity and both types of value. The utilitarian and hedonic value of TRMP significantly influenced both the exploitative and explorative use of TRMP. Travel-related mobile applications are dramatically increased in the tourism field. This research sheds light on TRMP usage, as a new and smart device, from a user’s perspective based on the affordance theory. This study represents a valuable direction regarding the emerging travel-related online platforms in tourism.

Keywords
travel-related mini-program (TRMP); affordance theory; utilitarian value; hedonic value; exploitative use; explorative use

1. Introduction
The emergence of smartphones has provided a lot of convenience for travel. Various APPs began to spring up in the last ten years, among which travel-related APPs are top-rated and ranked 7th in the mobile APPs download ranking (R-Style Lab, 2018). Although travel-related APPs play an increasingly important role in travel, the APPs are used less frequently due to travel’s low-frequency nature. (Cheng, Ren, Hong, Nam, & Koo, 2019). Travel-related APPs have used an average of only 2.6 times per week and keep 45% of their users over 90 days (GoodWorkLabs, 2016).

WeChat mini-program (WMP) was released by WeChat in 2017, the giant in China’s instant messaging industry, WeChat is a free instant messaging service provider released by Tencent in 2011. It also incorporates mobile payments, social network services (SNSs), financial management, public services, charity services, and other services provided by third-party operators, such as food delivery. Therefore, WeChat has built an online ecosystem around Chinese people’s lives. In the second quarter of 2016, more than 94% of smartphone users installed WeChat, and monthly active users reached 806 million in China (Tencent Big Data, 2016).

The WMP has several different features comparing to other APPs. It does not need to be installed or uninstalled, is fast and lightweight, and has no complicated features and advertisement push. Thus, WMP can fit the needs of people who travel 1 to 2 times a year. Several online travel agents and travel companies have launched their mini-programs to attract travelers (e.g., Booking.com, Airbnb, C-trip, Qunar.com, TripAdvisor). More than 1 million mini-programs have been launched, covering 200 categories, and daily users have reached more than 200 million (QPSoftware, 2019). Travel-related mini-programs (TRMP) have abandoned the burdensome procedures of using past Internet products and have done a better job than websites and general apps of elevating the user experience. Additionally, TRMPs provide various functions of general apps and integrate special features such as authentication, mobile payment, information sharing, and social community.

Under the importance of mobile devices in tourism, recent studies have focused on mobile devices such as smartphones (Tussyadiah & Zach, 2012; Wang, Xiang, & Fesenmaier, 2016) and travel-related APPs (Dickinson et al., 2014; Wang et al., 2016). In travel-related APPs, numerous studies have concentrated on the use patterns and adoption of the APPs and attractive design for users; however, little is known about the lower frequency of travel APPs usage. In addition, affordance theory can explain the uses and achievements of information systems and technology based on the relationships between individuals/organizations and technical characteristics (Majchrzak & Markus, 2012). It can also incorporate information technology artifacts into analysis and align with how the
information technology practitioners think about their challenges (Volkoff & Strong, 2017). Therefore, this study examines the relationships among affordances provided by TRMP, and constraints while using those mini-programs, and the travelers’ perceived value of TRMP usage.

2. Literature Review

2.1 Affordance Theory

Gibson (1979) proposed the affordance theory in 1979, representing the physical relationship between an actor and physical artifacts in the world, reflecting possible actions on those artifacts. Norman (1988) firstly adopted the affordance theory into the human-computer interaction field. He viewed affordance as the product’s design feature that shows how the product is used. Norman (1988) thought that affordance relies more on the actor’s experience and knowledge, and it can predict actors’ behavior and suggest a range of possibilities. The central principle of affordance theory is that technological capabilities are not inherent to a specific technology but exist as part of the association between users and the technological artifacts within a particular domain (Treem & Leonardi, 2013). During the interaction between humans and machines, a human user performs cognitive, physical, and sensory actions and requires affordances to help with each (Harton, 2003). Based on previous studies, Harton (2003) classified affordance as four types: cognitive, physical, sensory, and functional affordance, according to its role in supporting users during interactions. (Table 1).

<table>
<thead>
<tr>
<th>Affordance Type</th>
<th>Description</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cognitive affordance</td>
<td>A design feature that helps users in knowing something</td>
<td>A button label that helps users know what will happen if they click on it</td>
</tr>
<tr>
<td>Physical affordance</td>
<td>A design feature that helps users in doing a physical action in the interface</td>
<td>A button that is large enough so that users can click on it accurately</td>
</tr>
<tr>
<td>Sensory affordance</td>
<td>A design feature that helps users sense something (especially cognitive affordances and physical affordances)</td>
<td>A label font size large enough to read easily</td>
</tr>
<tr>
<td>Functional affordance</td>
<td>A design feature that helps users accomplish work (i.e., the usefulness of a system function)</td>
<td>The internal system ability to sort a series of numbers (invoked by users clicking on the Sort button)</td>
</tr>
</tbody>
</table>

Source: Harton (2003, p. 323)

2.2 Perceived Value

Perceived value was defined as “the consumer’s overall assessment of the utility of a product (or service) based on perceptions of what is received and what is given” (Zeithaml, 1988, p. 14). To better understand the perceived value, numerous scholars are beginning to examine perceived value by adopting a multidimensional approach (Chiu, Wang, Fang, & Huang, 2014). Thus, the value theory is classified into utilitarian and hedonic value subsystems (Chiu et al., 2014; Chung & Koo, 2015). Utilitarian value is defined as an overall assessment of functional benefits and sacrifices (Overby & Lee, 2006). It is related to tools, rational, functional, cognitive, and means of end activities, while the hedonic value is associated with entertainment and the emotional worth of consumption (Chung & Koo, 2015). However, hedonic value is defined as an overall assessment of experiential benefits and sacrifices, such as entertainment and escapism (Overby & Lee, 2006). In this study, the utilitarian value of TRMP is defined as the overall assessment of functional benefits and sacrifices of using TRMP; In contrast, the hedonic value of TRMP is defined as the comprehensive evaluation of the experiential benefits and sacrifices of using TRMP.

2.3 Technology Constraint

Constraints and affordances are viewed as relational concepts regarded as the potential interactions between individuals and technology (Majchrzak & Markus, 2012). The affordance of technology refers to an individual or organization’s action potential or organization operates a technology or information system with a specific purpose. In contrast, technology constraint refers to how an individual or organization can be restrained while using technology or a system with a particular goal (Majchrzak & Markus, 2012). The existent research related to technology constraints—distrust, perceived risk, and unfamiliarity—are the three factors that appeared most frequently (Barkmann et al., 2008; Sillince & Shipton, 2013; So, Oh, & Min, 2018). TRMP is a new technology introduced to the tourism field; the research model’s constraints include three dimensions.

Trust represents consumers’ willingness to depend on an exchange partner (Moorman, Zaltman, & Deshpande, 1992). However, distrust of the Airbnb service providers and the host restricted travelers from choosing Airbnb (So et al., 2018). Tussyadiah and Pesonen (2018) defined distrust as the lack of interpersonal trust between host and guest and lack of trust toward technology. In this study, distrust can be defined as the lack of interpersonal trust between travelers and TRMP service providers and the lack of trust toward new technology.

Perceived risk refers to the consumer’s perception of the potential for adverse outcomes in the purchase context, which is one of the main barriers for consumers to be unwilling to purchase behavior (Park & Tussyadiah, 2017). Perceived risk exists in mobile shopping because consumers cannot obtain evidence of the difference between pre-purchase assessments and actual product qualities. Besides, since mobile devices represented by smartphones are viewed as self-service technologies, mobile shopping requires consumers to take considerable responsibility (Cunningham, Gerlach, Harper, & Young, 2005). In this study, perceived risk can be defined as the subjectively determined expectation of loss using TRMP during the trips.

Given that WMP is a relatively new technology introduced to the tourism industry, travelers may have limited knowledge and information about this alternative service provider. The lack of knowledge, information, or ability to use can be perceived as a constraint in using TRMP during a trip (Tussyadiah & Pesonen, 2018). As a very fast-changing technology field, of course, many scholars have done a lot of research on people’s unfamiliarity with technology. Cooper, Taft, and Thelem (2004) indicated that unfamiliarity with technology is one of the main barriers to learning with adopting the technology. Based on previous research, unfamiliarity with TRMP is defined as a lack of knowledge or ability to use TRMP for this research.
2.4 Exploratory/Exploitative Use

The concepts of exploration and exploitation are generally adopted in the organizational learning context and extended to individual learning and decision-making (Huang, Goo, Nam, & Yoo, 2017). For individuals, exploration is a deviation from existing tasks and seeking alternatives, while exploitation refers to a behavior that optimizes the performance in the current tasks (Aston-Jones & Cohen, 2005). In the information system adoption context, Burton-Jones and Straub (2006) claimed that explorative use is associated with seeking new and different system uses, while exploitative use involves the refinement of the old system and existing knowledge. Koo, Chung, and Kim (2015) indicated that user competence and perceived usefulness are positively related to the smartphone’s explorative and exploitative use. In contrast, perceived ease of use only influences explorative use. Huang et al. (2017) argued that explorative use of smart tourism technology (STT) strongly affects travel experience satisfaction and exploitative use of STT has a positive effect on transaction satisfaction. Considering the feature of TRMP, the current study defined the explorative use of TRMP as seeking new and different uses (e.g., translator) of the TRMP; exploitative use of TRMP as essential functions (e.g., booking) provided by TRMP.

3. Methodology

A research model is proposed in Figure 1. The measurements consist of six constructs: affordance, constraint, perceived utilitarian value, perceived hedonic value, explorative use, and exploitative use. The items of four types of affordances were derived from Hartson (2003); perceived risk and distrust were adapted from the research of So et al. (2018) and Mao and Lyu (2017); unfamiliarity was derived from Mao and Lyu (2017). The perceived utilitarian value and hedonic value were derived from Ozturk, Nusair, Okumus, and Hua (2016). Finally, the explorative and exploitative use items were Adapted from Koo et al. (2015). Each item was measured using a 7-point Likert scale ranging from strongly disagree to agree strongly.

Fig. 1. Research model

4. Hypotheses Development

4.1 Relationships Between Affordance and Perceived Value

The technology affordance theory can describe how individuals understand and approach technology differently (Leonardi, Nardi, & Kallinikos, 2012). Chiu et al. (2014) studied customers’ repeat purchase intentions in the B2C e-commerce context and suggested that product information positively affects utilitarian value. Kim and Han (2011) also examined the role of utilitarian and hedonic values and their antecedents in a mobile data service environment. The results indicated that information quality positively influences both utilitarian and hedonic values. During the interaction between humans and machines, a human user performs cognitive, physical, and sensory actions and looks for these kinds of affordances to help achieve the goal (Hartson, 2003). Accordingly, the hypotheses are proposed as follows:

H1: The physical affordance provided by TRMP has a positive effect on utilitarian value (H1a) and hedonic value (H1b) of TRMP.

Cognitive affordance can be used to evaluate during the use of any technology or machine (Hartson, 2003). As a cognitive concept, value helps to describe the user’s decision-making and usage behavior, and as another cognitive concept, cognitive affordance helps the user solve problems. As a higher-level cognitive process, problem-solving interacts with many other cognitive processes, such as decision-making, inferring, and evaluating (Wang & Chiew, 2010). In other words, cognitive affordance affects the user’s evaluating behavior through the decision-making process. Therefore, the hypotheses of cognitive affordance and perceived value of TRMP can be proposed as follows:

H2: The cognitive affordance provided by TRMP has a positive effect on utilitarian value (H2a) and hedonic value (H2b) of TRMP.
Hartson (2003) argued that sensory affordance is needed in the stage of intention to act, execution of the action sequence, and to perceive the state of the world in the steps of the action model. That is to say, sensory affordance helps the user plan and execute the action of using technology and perceiving the state of these activities. Sensory affordance is in the position supporting cognitive affordance and physical affordance. For example, the button’s font size and color may affect text legibility; thus, evaluate the technology. Moreover, Kim and Forsythe (2009) found that sensory enabling technologies can be increasing the hedonic value of the online shopping process by reducing perceived product risk in an online shopping context. Thus, we hypothesize:

H3: The sensory affordance provided by TRMP has a positive effect on utilitarian value (H3a) and hedonic value (H3b) of TRMP.

Furthermore, Korda and Snoj (2010) examined the development, validity, and reliability of perceived service quality in retail banking and its relationship with perceived value and customer satisfaction. Results indicated that service quality significantly influences perceived value in the context of retail banking. Moreover, Hu, Kandampully, and Juwaheer (2009) studied the relationships and impacts of service quality, perceived value, customer satisfaction, and image by adopting functional quality and technical quality two-dimension approach. Results revealed that a significant effect exists between service quality and perceived value. Therefore, the hypotheses are as follows:

H4: The functional affordance provided by TRMP has a positive effect on utilitarian value (H4a) and hedonic value (H4b) of TRMP.

4.2 Relationships Between Constraint and Perceived Value

Among the previous studies, distrust towards the host and technology is one of the barriers to peer-to-peer accommodation among American travelers (Tussyadiah & Pesonen, 2018). Järveläinen and Puhakainen (2004) also indicated that the barriers for transference to e-commerce might be caused by distrust of the online booking system itself or in the individual’s skills with the system. Furthermore, (un)familiarity and (dis)trust play an important role in significant nature (Perrea, Grunert, & Krystallis, 2015). Sirdeshmukh, Singh, and Sabol (2002) examined consumer trust, value, and loyalty in relational exchanges; findings revealed that value completely mediates the effect of frontline employee trust on loyalty in the retailing context. Thus, we hypothesize:

H5: The distrust towards TRMP has a negative effect on utilitarian value (H5a) and hedonic value (H5b) of TRMP.

Also, Liang, Choi, and Joppe (2018) studied the influence on consumer repurchase intention of peer-to-peer accommodation. They found that the perceived risk of using Airbnb is negatively related to perceived value. Yang, Yu, Zo, and Choi (2016) showed that both performance and financial risk have negative effects on the perceived value of wearable devices. Kleijnjen, De Ruyter, and Wetzels (2007) revealed that perceived risk negatively affects the perceived value of mobile channels. Moreover, perceived value is a function of benefits and costs in an online shopping context, and time, effort, and price can be understood as the costs of online shopping. Perceived risk can be viewed as a significant online shopping cost since it can change users’ overall value towards online shopping (Chiu et al., 2014). Therefore, we hypothesize:

H6: The perceived risk of using TRMP has a negative effect on utilitarian value (H6a) and hedonic value (H6b) of TRMP.

Unfamiliarity with an environmental good can result in some biases such as information bias and methodological misspecification bias, which leads to distorted valuation (Barkmann et al., 2008). Also, a customer who has higher familiarity with online store attributes leads to greater online perceived value and helps them make a decision, resulting in more utility (Wu & Chang, 2016). On the contrary, customers’ unfamiliarity with online or offline channel attributes negatively affects perceived value. Therefore, the hypotheses are proposed as follows:

H7: The unfamiliarity with TRMP has a negative effect on utilitarian value (H7a) and hedonic value (H7b) of TRMP.

4.3 Relationships Between Perceived Value and Exploratory/Exploitative Use

Since travelers want to maximize value in the decision-making process, they are reluctant to use things with lower perceived value (Chung & Koo, 2015). The utilitarian value and hedonic value reflect the benefits from a cognitive perspective in a mobile shopping context (Kim, Li, & Kim, 2015). Consumers who seek utilitarian value tend to look for vital information to consider products and services before actual purchase (Deligray, Gillpatrick, Marusic, Pantelic, & Kuruvilla, 2010). Consumers who seek hedonic value tend to search for different experiences that have no connection to product purchasing behavior (Kim et al., 2015). In TRMP context, users who seek utilitarian value tend to look for information related to TRMP, and users who look for hedonic value tend to seek different experiences.

Chung and Koo (2015) showed that perceived value and enjoyment (perceived hedonic value) are positively related to the travel information searches in social media usage. Moreover, information reliability on social media usage for travel information search is fully mediated by perceived value. Compared to new users, experienced users are more likely to consider technology’s utilitarian value on continued usage (Limayem, Hirt, & Cheung, 2007). Venkatesh, Speier, and Morris (2002) also showed that the utilitarian value of technology (as represented by perceived usefulness) is a predictor of continued technology usage. Since the usefulness and usage of technology need to be captured at different aspects of functions, and concerning explorative and exploitative use, perceived usefulness can be viewed as a value-adding attribute of smartphone usage (Koo et al., 2015). Moreover, Kim et al. (2015) showed that both utilitarian value and hedonic value have significant influences on mobile shopping usage. Chong, Zhang, Lai, and Nie (2012) examined mobile internet acceptance from a value-based view and found that perceived value affects intention to reuse mobile services. Yang (2010) found that the hedonic or entertainment aspect of mobile shopping services is the most important driver of the US consumers’ intention to use them. Accordingly, we hypothesize:

H8: The utilitarian value of TRMP has a positive effect on exploitative use (H8a) and explorative use (H8b) of TRMP.

H9: The hedonic value of TRMP has a positive effect on exploitative use (H9a) and explorative use (H9b) of TRMP.

4.4 Data Collection

The dataset was collected through an online questionnaire service company, namely Wenjuanxing.Com, the earliest and the largest online survey, examination, and voting platform in China. The online survey was conducted for 15 days, from July 16 to July 31, 2019. This research is focused on the TRMP user, a screening question to filter only the respondents who have had use TRMP...
at least once. A total of 651 questionnaires were received, and 448 (68.8%) were analyzed for this research. The data were analyzed using Statistical Package for the Social Sciences 23 and SmartPLS 3.0. First, descriptive statistics analysis was conducted to describe the demographic and general characteristics of the respondents. Second, normality tests of the constructs in the model were performed. Third, SmartPLS was used to analyze the structural equation modeling (SEM). The reason for using SmartPLS is that partial least squares (PLS) are suitable to analyze a complicated model that consists of many manifest and latent variables (Henseler & Sarstedt, 2015). SmartPLS does not require strict assumptions about the distribution of variables, which is the most appropriate way to examine data with asymmetric or non-standard distribution (Falk & Miller, 1992). It also requires less residual distribution and sample size, which is an advantage of a component-based approach (Gefen, Straub, & Boudreau, 2000). Moreover, to eliminate the standard error of the hypothesis test, it is recommended to use a bootstrap process of at least 5,000 bootstrap samples so that the data samples used in the study have a reasonable representation of the population distribution; the coefficient weights between the variables can be calculated (Hair, Ringle, & Sarstedt, 2011).

## 5. Results

### 5.1 Demographic Characteristics

Of the 448 respondents, 60.3% were female, and 39.7% were male. Almost half of the respondents (49.8%) are at the age of 20 to 29, followed by 30-39 (38.6%). Most respondents (43.3%) used TRMP more than five times (Table 2).

### Table 2. Demographic characteristics of respondents (n=448)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Frequency (%)</th>
<th>Variables</th>
<th>Frequency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td><strong>Destination of the most recent trip</strong></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>178 (39.7)</td>
<td>Domestic</td>
<td>416 (92.9)</td>
</tr>
<tr>
<td>Female</td>
<td>270 (60.3)</td>
<td>Abroad</td>
<td>32 (7.1)</td>
</tr>
<tr>
<td><strong>Travel party in the most recent trip</strong></td>
<td></td>
<td><strong>Previous experience of using TRMP</strong></td>
<td></td>
</tr>
<tr>
<td>Alone</td>
<td>48 (10.7)</td>
<td>First time</td>
<td>56 (12.5)</td>
</tr>
<tr>
<td>Couple</td>
<td>146 (32.6)</td>
<td>2 times</td>
<td>68 (15.2)</td>
</tr>
<tr>
<td>Family</td>
<td>101 (22.5)</td>
<td>3 times</td>
<td>78 (17.4)</td>
</tr>
<tr>
<td>Friends</td>
<td>108 (24.1)</td>
<td>4 times</td>
<td>52 (11.6)</td>
</tr>
<tr>
<td>Colleague</td>
<td>22 (4.9)</td>
<td>Over 5 times</td>
<td>194 (43.3)</td>
</tr>
<tr>
<td>Schoolmate</td>
<td>14 (3.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>9 (2.0)</td>
<td><strong>Number of trips per year</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Occupation</strong></td>
<td></td>
<td>Never</td>
<td>9 (2.0)</td>
</tr>
<tr>
<td>Student</td>
<td>59 (12.2)</td>
<td>1-2</td>
<td>185 (41.3)</td>
</tr>
<tr>
<td>Administrative/Clerical job</td>
<td>124 (27.7)</td>
<td>3-4</td>
<td>186 (41.5)</td>
</tr>
<tr>
<td>Professional/specialized job</td>
<td>91 (20.3)</td>
<td>5 or more</td>
<td>68 (15.2)</td>
</tr>
<tr>
<td>Self-employed</td>
<td>32 (7.1)</td>
<td><strong>Purpose of the most recent trip</strong></td>
<td></td>
</tr>
<tr>
<td>Sales/Services position</td>
<td>47 (10.5)</td>
<td>Sightseeing (Study, Vacation)</td>
<td>358 (79.9)</td>
</tr>
<tr>
<td>worker</td>
<td>42 (9.4)</td>
<td>Business</td>
<td>35 (7.8)</td>
</tr>
<tr>
<td>Homemaker</td>
<td>11 (2.5)</td>
<td>Visiting Friends or Relations</td>
<td>31 (6.9)</td>
</tr>
<tr>
<td>Other</td>
<td>42 (9.4)</td>
<td>Others</td>
<td>24 (5.4)</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td><strong>Length of the most recent trip</strong></td>
<td></td>
</tr>
<tr>
<td>10-19</td>
<td>10 (2.2)</td>
<td>1 night</td>
<td>37 (8.3)</td>
</tr>
<tr>
<td>20-29</td>
<td>223 (49.8)</td>
<td>2-3 nights</td>
<td>205 (45.8)</td>
</tr>
<tr>
<td>30-39</td>
<td>173 (38.6)</td>
<td>4-5 nights</td>
<td>130 (29.0)</td>
</tr>
<tr>
<td>40-49</td>
<td>32 (7.1)</td>
<td>6-7 nights</td>
<td>48 (10.7)</td>
</tr>
<tr>
<td>50-59</td>
<td>9 (2.0)</td>
<td>8-9 nights</td>
<td>10 (2.2)</td>
</tr>
<tr>
<td>60 and above</td>
<td>1 (0.2)</td>
<td>Over 10 nights</td>
<td>18 (4.0)</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td><strong>Use of travel-related programs</strong></td>
<td></td>
</tr>
<tr>
<td>High School Graduate</td>
<td>17 (3.8)</td>
<td>C-trip</td>
<td>391 (87.3)</td>
</tr>
<tr>
<td>College Graduate</td>
<td>34 (7.6)</td>
<td>Tongcheng Lvyou</td>
<td>210 (46.9)</td>
</tr>
<tr>
<td>Master Degree</td>
<td>324 (72.3)</td>
<td>Yilong</td>
<td>136 (30.4)</td>
</tr>
<tr>
<td>Doctoral Degree</td>
<td>54 (12.1)</td>
<td>Qunar</td>
<td>265 (59.2)</td>
</tr>
<tr>
<td>Other</td>
<td>19 (4.2)</td>
<td>Qiongyou</td>
<td>37 (8.3)</td>
</tr>
<tr>
<td><strong>Annual salary</strong></td>
<td></td>
<td>Tuniu</td>
<td>155 (34.6)</td>
</tr>
<tr>
<td>Less than 50,000 Yuan</td>
<td>97 (21.7)</td>
<td>Mafengwo</td>
<td>106 (23.7)</td>
</tr>
<tr>
<td>50,001~60,000 Yuan</td>
<td>51 (11.4)</td>
<td>Xiaozhu Minsu</td>
<td>61 (13.6)</td>
</tr>
<tr>
<td>60,001~70,000 Yuan</td>
<td>40 (8.9)</td>
<td>Tujjawang</td>
<td>49 (10.9)</td>
</tr>
<tr>
<td>70,001~80,000 Yuan</td>
<td>41 (9.2)</td>
<td>Airbnb</td>
<td>111 (24.8)</td>
</tr>
<tr>
<td>80,001~90,000 Yuan</td>
<td>44 (9.8)</td>
<td>Booking</td>
<td>25 (5.6)</td>
</tr>
<tr>
<td>90,001~100,000 Yuan</td>
<td>68 (15.2)</td>
<td>TripAdvisor</td>
<td>18 (4.0)</td>
</tr>
<tr>
<td>More than 100,000 Yuan</td>
<td>107 (23.9)</td>
<td>Lymama</td>
<td>48 (10.7)</td>
</tr>
</tbody>
</table>

### 5.1.1 Measurement Model

This study’s measurement model was evaluated through validity and reliability. First, the AVE’s convergent validity (average variance extracted) and CR (composite reliability) value were evaluated. The factor loadings value of all items is more significant than 0.7, which satisfies the excellent conditions. The range of AVE values is between 0.593 to 0.771, higher than 0.5 suggested by Hair et al. (2011). The CR values ranged from 0.841 to 0.918, were greater than 0.7. Then, the reliability of the model was tested by Cronbach’s α. The results showed that the values of Cronbach’s α ranged from 0.717 to 0.853, which exceeded 0.7.
recommended by Nunnally (1994). These results confirmed the convergent validity and reliability of the measurement model (Table 3).

The discriminant validity of the measurement model was verified by comparing the root of AVE value and the correlation values (Carmines & Zeller, 1979). Given that all of the correlations with any other latent constructs were smaller than their AVE root values, the discriminant validity was demonstrated (Table 4).

Table 3. Analysis of reliability and convergent validity

<table>
<thead>
<tr>
<th>Items</th>
<th>Factor Loadings</th>
<th>CR</th>
<th>Cronbach’s α</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Physical Affordance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>When using a TRMP, the buttons on the screen are easy to select or click.</td>
<td>0.802</td>
<td>0.841</td>
<td>0.717</td>
<td>0.638</td>
</tr>
<tr>
<td>When using a TRMP, it will immediately jump to the next page after clicking a button.</td>
<td>0.790</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>When using a TRMP, the page is very smooth and there is no stuttering.</td>
<td>0.804</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Cognitive Affordance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>When using a TRMP, I know exactly what each button on the screen does.</td>
<td>0.840</td>
<td>0.855</td>
<td>0.746</td>
<td>0.663</td>
</tr>
<tr>
<td>When using a TRMP, I know exactly what will happen after clicking a button.</td>
<td>0.799</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>When using a TRMP, the role of each button on the screen is easy to distinguish.</td>
<td>0.803</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Sensory Affordance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>When using a TRMP, I sense that the size and color of the buttons are well designed.</td>
<td>0.811</td>
<td>0.849</td>
<td>0.733</td>
<td>0.652</td>
</tr>
<tr>
<td>When using a TRMP, I sense that the font and size of the text on the button are well designed.</td>
<td>0.807</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>When using a TRMP, I sense that the buttons on the screen are easy to see.</td>
<td>0.804</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Functional Affordance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>When using a TRMP, I feel that it is fully functional.</td>
<td>0.797</td>
<td>0.852</td>
<td>0.740</td>
<td>0.658</td>
</tr>
<tr>
<td>When using a TRMP, I can find products or services that meet my needs.</td>
<td>0.843</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I feel that using a TRMP can be very useful for my travels.</td>
<td>0.793</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Distrust</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compared to general APPs, I do not trust the TRMP.</td>
<td>0.828</td>
<td>0.855</td>
<td>0.780</td>
<td>0.695</td>
</tr>
<tr>
<td>I do not trust online business transactions with TRMP.</td>
<td>0.876</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I concern about privacy while using TRMP.</td>
<td>0.795</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Perceived Risk</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Whether TRMP offers the money’s worth is uncertain.</td>
<td>0.873</td>
<td>0.918</td>
<td>0.881</td>
<td>0.738</td>
</tr>
<tr>
<td>Whether TRMP offers expected quality is uncertain.</td>
<td>0.890</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Whether TRMP offers guests a good image is uncertain.</td>
<td>0.872</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRMP would not be effective as I think.</td>
<td>0.800</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Unfamiliarity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I am NOT familiar with TRMP.</td>
<td>0.900</td>
<td>0.910</td>
<td>0.853</td>
<td>0.771</td>
</tr>
<tr>
<td>I am NOT experienced with TRMP.</td>
<td>0.833</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I am NOT knowledgeable about TRMP.</td>
<td>0.900</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Utilitarian Value of TRMP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I accomplished just what I wanted to with TRMP.</td>
<td>0.818</td>
<td>0.881</td>
<td>0.798</td>
<td>0.713</td>
</tr>
<tr>
<td>While I was using TRMP, I found just the tourism products or services I was looking for.</td>
<td>0.851</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>With TRMP, I could find the tourism products or services that I really needed.</td>
<td>0.863</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Hedonic Value of TRMP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRMP is fun to use.</td>
<td>0.856</td>
<td>0.865</td>
<td>0.764</td>
<td>0.682</td>
</tr>
<tr>
<td>The actual process of TRMP is pleasant.</td>
<td>0.744</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Using TRMP is enjoyable.</td>
<td>0.871</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Exploitative Use of TRMP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I fully use the available TRMP features to complete my travels.</td>
<td>0.825</td>
<td>0.883</td>
<td>0.824</td>
<td>0.654</td>
</tr>
<tr>
<td>I use most of the available TRMP features in designing my travels.</td>
<td>0.826</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I make thorough use of the available TRMP features to accommodate my travels.</td>
<td>0.813</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I use all the available TRMP features to help me with my travels.</td>
<td>0.769</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Explorative Use of TRMP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>People like me would use TRMP.</td>
<td>0.780</td>
<td>0.853</td>
<td>0.771</td>
<td>0.593</td>
</tr>
<tr>
<td>Using TRMP would improve my image among my friends and peers.</td>
<td>0.742</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>People who are important to me probably think that I should use TRMP.</td>
<td>0.762</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>My friends and peers would expect me to use TRMP.</td>
<td>0.795</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 4. Discriminant validity of factors

<table>
<thead>
<tr>
<th>Factor</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Cognitive Affordance</td>
<td>0.814</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Distrust</td>
<td>-0.28</td>
<td>0.834</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Exploitative Use of TRMP</td>
<td>0.502</td>
<td>-0.359</td>
<td>0.77</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Explosive Use of TRMP</td>
<td>0.514</td>
<td>-0.404</td>
<td>0.675</td>
<td>0.809</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Functional Affordance</td>
<td>0.643</td>
<td>-0.368</td>
<td>0.529</td>
<td>0.595</td>
<td>0.811</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Hedonic Value of TRMP</td>
<td>0.555</td>
<td>-0.378</td>
<td>0.63</td>
<td>0.647</td>
<td>0.607</td>
<td>0.826</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Physical Affordance</td>
<td>0.57</td>
<td>-0.285</td>
<td>0.414</td>
<td>0.519</td>
<td>0.604</td>
<td>0.544</td>
<td>0.799</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Perceived Risk</td>
<td>-0.303</td>
<td>0.694</td>
<td>-0.312</td>
<td>-0.376</td>
<td>-0.354</td>
<td>-0.376</td>
<td>-0.308</td>
<td>0.859</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. Sensory Affordance</td>
<td>0.519</td>
<td>-0.241</td>
<td>0.474</td>
<td>0.525</td>
<td>0.522</td>
<td>0.522</td>
<td>-0.25</td>
<td>0.807</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10. Unfamiliarity</td>
<td>-0.327</td>
<td>0.528</td>
<td>-0.389</td>
<td>-0.468</td>
<td>-0.362</td>
<td>-0.416</td>
<td>-0.318</td>
<td>0.53</td>
<td>-0.293</td>
<td>0.878</td>
<td></td>
</tr>
<tr>
<td>11. Utilitarian Value of TRMP</td>
<td>0.552</td>
<td>-0.382</td>
<td>0.656</td>
<td>0.697</td>
<td>0.663</td>
<td>0.679</td>
<td>0.572</td>
<td>-0.38</td>
<td>0.543</td>
<td>-0.477</td>
<td>0.844</td>
</tr>
</tbody>
</table>

5.1.2 Results of the Structural Model

SmartPLS was used to test the structural model. To ensure the precision of estimation, a bootstrapping procedure with a resampling of 5,000 subsamples was used to determine the statistical significance of the parameter estimates. As for the first antecedent construct of the value of TRMP, significant relationships existed between physical affordance and both utilitarian value ($\beta=0.154, p<0.05$) and hedonic value ($\beta=0.147, p<0.01$) of TRMP, supporting H1a and H1b. There was no significant influence between cognitive affordance and utilitarian value. However, cognitive affordance could influence utilitarian value significantly ($\beta=0.151, p<0.01$). Thus, H2a could be supported, while H2b could not be supported. In addition, sensory affordance also positively affected both utilitarian value ($\beta=0.175, p<0.001$) and hedonic value ($\beta=0.177, p<0.001$), supporting H3a and H3b. Moreover, both utilitarian value ($\beta=0.340, p<0.001$) and hedonic value ($\beta=0.245, p<0.001$) were positively influenced by functional affordance, which supported both H4a and H4b.

In the second antecedent variable of the value of TRMP, the constraint consisted of three factors: distrust, perceived risk, and unfamiliarity. Distrust did not affect both utilitarian value and hedonic value, not supporting H5a and H5b. Similarly, perceived risk also had no effects on both types of values, not supporting H6a and H6b. However, H7a and H7b could be supported since unfamiliarity negatively affected both utilitarian value ($\beta=-0.205, p<0.001$) and hedonic value ($\beta=-0.121, p<0.05$) significantly.

The results also demonstrated the relationships between two different types of value of TRMP and two kinds of use of TRMP. The utilitarian value of TRMP significantly influenced both exploitative use ($\beta=0.478, p<0.001$) and explorative use ($\beta=0.423, p<0.001$) of TRMP, supporting H8a and H8b. Significant relationships existed between the hedonic value of TRMP and both exploitative use ($\beta=0.343, p<0.001$) and explorative use ($\beta=0.343, p<0.001$) and H9a and H9b were supported. Additionally, the results indicated that the R2 value of the dependent constructs was 0.542 for exploitative use and 0.493 for explorative use. Consequently, most of the hypotheses were supported (see Figure 2, Table 5).

![Fig. 2. Results of the structure model](image-url)
The current study examines the relationships among affordances, constraints, value provided by TRMP from the affordance theory. Findings indicated that physical affordance, sensory affordance, and functional affordance positively affected the utilitarian value of TRMP. Since affordance can be viewed as qualities in ontology, this finding was consistent with the extant study that e-service quality or information quality significantly affect perceived value (Kim & Niehm, 2009; Pearson, Tadisina, & Griffin, 2012; Wang & Wang, 2010). However, cognitive affordance had no significant influence on utilitarian value. As for the hedonic value, all of the four types of affordance had substantial effects on it. In the second antecedent variable of the value of TRMP, there were negative relationships between distrust and both kinds of value; however, they were not significant.

Moreover, the same situation existed for perceived risk. It is because users trust WeChat and believe that there is no risk in the platform provided by WeChat that is the giant of social tools in China. As another constraint factor, unfamiliarity negatively affected both utilitarian value and hedonic value significantly. This finding was consistent with the previous studies that unfamiliarity has a negative relationship with perceived value (Barkmann et al., 2008; Perrea et al., 2015; Wu & Chang, 2016). Although people are willing to believe in WeChat, people are still not very familiar with mini-programs as new stuff. Thus, for TRMP, unfamiliarity will bring negative impacts on its values.

The results also demonstrated the relationships between two different types of value and two kinds of use of TRMP. The utilitarian value of TRMP significantly influenced both exploitative use and explorative use of TRMP. Besides, significant relationships existed between the hedonic value of TRMP and both exploitative and explorative use. Findings were consistent with the previous studies that technology usage is influenced by perceived value (Chung & Koo, 2015; Limayem et al., 2007; Venkatesh et al., 2002).

This study offers some practical implications. The business opportunities of the TRMP can be said to be obvious. For travel companies, the business opportunity is to achieve user attraction and benefit conversion through a simple tool. Particularly for startups, TRMP is a good platform. Because the TRMP is built inside WeChat, users of WeChat are likely to become potential users. In the APP era, both the APP’s development cost and the cost of the acquisition of customers are high, but the TRMP may be able to improve this situation. More importantly, TRMP is unique. In the early stage of enterprise development, if an enterprise can register a large-flow hot word as a TRMP’s name, it will bring a lot of exposure and direct traffic to itself, which is more conducive to promoting tourism companies.

Furthermore, TRMPs are different from general APPs. They allow users, travel companies, and scenic spots to have more interactions with each other. For those travel companies, TRMPs make it easier for companies to offer customized products to travelers. The value of customization is handling complex journeys and using travel experience as a selling point. Travel companies need to strengthen their brand and train a new generation of travel consultants who need to attract tourists offline and online (especially social networks), offering rich and flexible products and relying on the mobile site to be on call. These travel consultants can keep in touch with the user through TRMPs, and they can quickly intervene when there is a problem in all stages of the trips. More importantly, recommending restaurants and destination products to travelers during the trip may be a good opportunity for upselling with this touchpoint. Travelers also have more interaction with online travel agencies (OTA) through APPs. The travelers write reviews or comments on OTAs’ APPs but do not directly give feedback to the attractions. However, TRMPs enable scenic spots to interact with travelers more. Travelers can provide feedback directly to the attractions so that the attractions can be improved as quickly as possible based on this feedback, thus travel experiences will also be improved.

However, there are several limitations. First, the survey was conducted for travelers who had used TRMP, and the findings were obtained from their perspective. However, to receive more meaningful results, a study from travel companies and attractions is needed. Second, TRMP is embedded in WeChat, and because the number of WeChat users is huge, users may be affected by friends or family members around them when using
TRMP. Therefore, the influence of social influence on the usage of TRMP should be considered in future studies. Additionally, most respondents to the survey were between 20 to 40 years old, but the age difference may exist to use this technology. Therefore, future research needs to consider the influence of age on the usage of TRMP.

Declaration of competing interests

None.

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