



# What makes tourists adopt smart hospitality? An inquiry beyond the technology acceptance model

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## ABSTRACT

Smart hospitality has become an attractive project in tourism. Extant research has studied smart technology as a contingency but has neglected to conceptualize smartness and investigate its consequences. This study conceptualizes and operationalizes smart hospitality and explores the relationships among smartness, perceived usefulness, perceived ease of use, overall image of a hotel and tourists' behavioral intention to stay in a smart hotel. The proposed model incorporated technology acceptance model (TAM) and image theory. With a sample of 348 respondents in Macau, this study tested the model using partial least squares path modeling (PLS-PM), which indicates that the proposed model fits the data. In spite of a high inter-construct correlation, the results showed that smartness does not have a direct effect on behavioral intention. According to mediation analysis, indirect effects made up of significant direct effects and assigned them to TAM, image theory, and a combination of both. This paper contributes to hospitality management theory by providing additional insight into smart hospitality, it demonstrates the applicability of PLS-PM with composite and common factor models in technological change research, and it suggests smartness as a business strategy that can change tourists' choices in practice.

## 1. Introduction

The improvement of living standards and changes in people's concepts of consumption have greatly promoted the development of tourism, which has further benefitted the hospitality industry. At the same time, competition in the hospitality industry has become increasingly intense, and service innovation has become an effective way to attract customers (Lai & Hung, 2017). New technologies such as the Internet and information systems have reshaped the hospitality industry and moved it into the intelligent era (Ip, Leung, & Law, 2011; Ivanov & Webster, 2019). In this context, the concept of smart hospitality is emerging and manifesting as a "fashion" (Leung, 2019). As the name implies, smart hospitality is smart and intelligent. With a range of the latest technologies working together, smart hospitality can provide a convenient and enjoyable environment for tourists and enhance their experience of staying in hospitality settings (Lai & Hung, 2017; Leung, 2019; Wu & Cheng, 2018).

Research on smart hospitality is growing and has studied the

phenomenon from various perspectives. Tourism investigates the requirements of smart technologies for personalized experiences in smart hospitality and considers the way that smart technology integration facilitates personalized tourism (Neuhofer, Buhalis, & Ladkin, 2015). Psychology investigates customers' behavioral intention to adopt new technologies in hospitality through beliefs such as trust and subjective norms (Kaushik, Agrawal, & Rahman, 2015). The technological perspective focuses on solutions to support smart hospitality (Leonidis, Korzi, Margetis, Grammenos, & Stephanidis, 2013). Many scholars are committed to designing interoperable and interconnected systems to automate daily activities in smart hospitality (Buhalis & Leung, 2018). These technology-rich systems can improve efficiency and add value for smart hospitality (Yu & Lee, 2009).

Tourism management mainly studies smart hospitality as a contingency, which means that it investigates tourist behavior under the contingency of smart hospitality (for instance, see Huang, Chang, Yu, and Chen (2019)). However, research on the consequences of smartness is still scarce. One likely reason for this scarcity of research is that many

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scholars regard “smart technologies” and “smart hospitality” as interchangeable concepts, although these two concepts are essentially different. “Smart technologies” usually correspond to an objective reality such as tangible products or services, while “smartness” is an abstraction and emphasizes tourists’ experience of automatically precise services via smart technologies (Li, Hu, Huang, & Duan, 2017). Perceived smartness is broader than smart technologies and can reflect the attitudes, feelings and intentions of tourists. When tourists decide to book smart hospitality, they are concerned about the “smartness” they are interested in. After checking in, guests can reach different smart technologies with multiple attributes, which form the composition of smartness. In addition to the theoretical framework of smart hospitality with technologies, it is equally important to pay attention to making smartness more service-oriented and customer-oriented (Wu & Cheng, 2018). In this sense, smart hospitality forms a class of hospitality, travel, and tourism instruments that can be viewed as artifacts designed by humans. Smartness is a design construct with diverse theoretical thinking toward different “smart” technology attributes, instead of an ontological entity or behavioral construct. It is necessary to measure it as a composite by paying tribute to the fact that all artifacts or abstractions thereof consist of more elementary components (Henseler, 2017). Smart hospitality has been measured in terms of input (smart products or services) (Li et al., 2017), output (automatic and sustainable smart hospitality) (Leonidis et al., 2013), process (system design) (Buhalis & Leung, 2018), or by a perceptual scale (tourists’ experience) (Kaushik et al., 2015). The composite of smartness in this research includes both input and perceptual of smart hospitality. As a result, it is important to realize that smartness in hospitality is more practical than theoretical (Jaremen, Jędrasiak, & Rapacz, 2016). Smartness quietly affects tourists’ impressions and experience, which in turn influences tourists’ behavioral intention.

In this research, we distinguish the concepts of “smart technology” and “smartness” and indicate the composition of smartness. Although smart hospitality has received much attention from scholars, we explore the role of smartness in smart hospitality. This study contributes to identify the causing factors of smartness and measure it as a composite construct. Based on the Technology Acceptance Model (TAM) and image theory, this study investigates the effects of smartness on perceived usefulness, perceived ease of use, overall image of hospitality and tourists’ behavioral intention. This study complements the literature on the relationship between the technical service of smart hospitality and customers’ intention to stay. In addition to an initial attempt to explain and evaluate the role of smartness, this study also provides a paradigm for designing technical artifacts using composite factors and Partial Least Squares Path Modeling (PLS-PM) in technological change research.

The remainder of the paper is organized as follows. We review the recent literature about smart hospitality and smartness in Section 2. Section 3 illustrates a conceptual model of the relationship between smartness and tourists’ behavioral intention based on the TAM and Image Theory. The description of the survey design and statistical analysis are presented in Section 4, and the study findings are presented in Section 5. We discuss the results in Section 6. Section 7 summarizes the paper and indicates future research directions.

## 2. Concept of smart hospitality

### 2.1. Smartness and smart technologies

“Smartness” consists of intelligent attributes that enrich objects’ functionalities and make them interoperable and interconnected, which in turn enables these objects to simplify and automate daily activities (Buhalis & Amaranggana, 2015; Buhalis & Leung, 2018). Obviously, the term “smartness” is associated with smart technology. Chervenak (1993) noted that advanced technology could lead to smartness over the past decade.

Smart technology is an essential foundation to achieve smartness. It refers to a technology with the ability to sense changes in the operating environment, for instance, condition or motion, and to enhance its functionalities to adapt to new, specific circumstances (Worden, Boulough, & Haywood, 2003). Information technology (IT), the Internet of things (IoT) and information and communication technologies (ICTs) are recognized as necessary smart technologies to construct a framework of interconnectivity and interoperability in smart systems (Buhalis & Leung, 2018; Porter & Heppelmann, 2014). Many studies have confirmed the value of IT (Karadag, Cobanoglu, & Dickinson, 2009; Neuhofer et al., 2015). IoT technology involves intelligent devices and objects connected by sensors via networks and enables people to search real-time information using mobile, wireless and sensor technologies (Sun & Ansari, 2016). It plays a critical role in the development of automation (Pavithra & Balakrishnan, 2015). ICT applications offer various possibilities for enhancing customers’ experiences with smart-phones, audio-visual technology, wearables, biometric technology and many more devices (Stankov, Filimonau, & Slivar, 2019; Van Winkle & Bueddefeld, 2020). It has changed tourists’ behavior in hospitality and tourism and induce tourists to make decisions by providing different ways of searching information (Law, Buhalis, & Cobanoglu, 2014).

### 2.2. Smart systems enabled by smart technologies

The pervasive use of high-tech, especially ICTs, in various urban domains (economy, mobility, environment, citizens, living and governance) aims to address social, economic and environmental issues, which leads to the emergence of the “smart city” (Höjer & Wangel, 2015). Smart cities effectively integrate physical, digital and human systems and aim to optimize resource utilization, promote sustainable development and improve residents’ quality of life (Carli, Dotoli, Pellegrino, & Ranieri, 2013). They offer a socioeconomic, ecofriendly and sustainable living environment for their citizens via smart technologies.

Internet-connected appliances, which constitute the IoT within home atmosphere, make infrastructure more digital and interactive, which leads to the emergence of “smart homes” (Dorri, Kanhere, Jurdak, & Gauravaram, 2017). Smart homes simplify daily life and provide protection for their occupants (Pavithra & Balakrishnan, 2015). In a smart home, people can control, monitor and manage the home environment through automated systems.

A tourism destination in combination with smart technologies transforms data derived from physical devices, social activities and government sources into a business ecosystem and provides tourists with value propositions, which leads to the emergence of “smart tourism” (Gretzel, Sigala, Xiang, & Koo, 2015). Smart tourism is an integrated industry with information management systems and can meet tourists’ personalized demand, improve tourists’ satisfaction and realize experience sharing between tourists (Jeong & Shin, 2019; Li et al., 2017). Tourists’ behavioral patterns become easier and more enjoyable with smart devices (Pradhan, Oh, & Lee, 2018).

### 2.3. Smart hospitality

The concept of “smart hospitality” refers to an intelligent hotel with integrated smart technologies that can satisfy guests’ functional and emotional needs and enable them to personally enhance their stay quality in a mobile environment (Jaremen et al., 2016; Wu & Cheng, 2018). Applications and implementations of smart technologies in smart hospitality have significant impacts on guests’ experience and behavior (Law et al., 2014; Stankov et al., 2019). Therefore, smart technology is the most important attribute to distinguish smart hospitality from general hospitality (Wu, Chin, & Liu, 2022).

Smart technologies facilitate tourists’ experiences while optimizing existing services (Neuhofer et al., 2015). Smart technology application focus not only on the accessibility of physical material but also on the availability of experience-related resources (Van Dijk, 2006). Yuksel,

Yuksel, and Bilim (2010) referred to technology dependence as a physical bond that meets guests' requirements by providing specific facilities and other functional devices. Jaremen et al. (2016) listed several well-known examples of smart hospitalities, such as The Upper House in Hong Kong (where guests receive an iPod Touch with a games, music and information about the hotel); Novotel München Messe (where reception provides ICTs equipped with touchscreens for tourists to search tourism information), and the Blow Up Hall, Poznań (where all room keys and cards have been replaced with iPhones). These applications not only meet demands of guests with high technology service, e.g. instant feedback, efficient check-in processing, unmanned service, and scene control, but enhance the competitiveness and attractiveness of smart hotels for visitors who expect "fashion" and digital environment. Meanwhile, these intelligent systems indicate that hospitality staffs should deliver effective service and on time communications with guest and colleagues in smart hotels.

Hence, smart technologies are key indicators that can contribute to "smartness" in the context of smart hospitality. To ensure that tourists are familiar with existing smart technologies, this study adopted the representative smart technologies to illustrate how smartness is constructed in smart hospitality. Specifically, four technologies: robots, scene control, audio-visual (AV) systems and mobile control (as shown in dashed box on the left part of Fig. 1), are selected based on the reasons as follows.

**Robots:** It is a trend for smart hospitality to deploy robots to automate daily service and provide fun for tourists through communication and interaction (Wood et al., 2013). Buhalis and Leung (2018) provided examples of smart hotels using robots, such as Hotel Jen of the Shangri-la group (where autonomous relay robots deliver items to guest rooms), Henn-na Hotel in Japan (where in-room robots provide automated customer service to save energy and reduce water), and Hilton hotels (where robots connected to a cognitive system with machine learning provide guests with hotel- and travel-related recommendations).

**Scene Control:** Based on smart systems, scene control can provide special personalized services and enable guests to adjust the accommodation environment with lighting sensors, voice commands, and touch-controlled panels. For example, guests can use voice commands to open the curtains, turn on the lights, and even switch TV channels (Kabadayi, Ali, Choi, Joosten, & Lu, 2019). These smart services bring convenience to guests while allowing them to relax.

**Audio-Visual (AV) System:** AV systems are a traditional category of smart hospitality that consists of various video display systems and innovative voice-controlled systems. The AV system can provide information in guests' native language and automatic self-service with adjustments of tone, lighting or sensor simulation. Raz (2016) reported that Wynn (Las Vegas, USA) became the first resort in the world with equipment from Amazon Echo, a smart speaker that constantly collects information about guests by big data and responds to voice comments

via the voice assistant Alexa. At Wynn, guests can control every aspect of the lighting, temperature and audio-visual components of hotel rooms.

**Mobile Control:** The widespread use of mobile devices, especially smartphones, and the development of the IoT have resulted in relevant mobile services in hospitality that enable tourists to use smartphones or tablets to control some facilities, such as door lock systems and AV systems. Tourists can experience a more convenient accommodation environment with no additional controlling devices. For instance, Hilton Worldwide provides a pioneering mobile service that allows guests to check in and select rooms by using floor plans available on mobile devices, tablets and laptops (Zhang, Seo, & Ahn, 2019).

### 3. A model of the acceptance of smart hospitality

Previous studies have indicated that the TAM has powerful ability to predict the usage intention of new technology. However, TAM cannot provide sufficient evidence to predict subject norm and acceptance of smart systems. TAM focuses on personal use of technology and ignores the influences of facilities' conditions, personal traits and social elements, which also encourage behavioral intention on using smart technologies. Many scholars combined TAM with other theories to explain people's behavior better (Huang, Backman, Backman, & Moore, 2013; Torres & Gerhart, 2019).

Image theory has been viewed as an influential theory to describe the relationship between destination image and visitation intention in tourism. Tourists are often impressed by the overall image of smart hospitality rather than objective smart technologies (Hunter, Chung, Gretzel, & Koo, 2015). To better understand the role of "smartness" produced by smart technologies in tourists' choice, this study designs a conceptual model combing TAM and image theory.

#### 3.1. Technology acceptance model (TAM)

The TAM consists of two major beliefs: perceived usefulness and perceived ease of use (Venkatesh & Davis, 2000), and is considered the most effective and commonly used theory to describe an individual's intention toward and behavior of technology usage (Lee, Kozar, & Larsen, 2003). Numerous empirical studies have examined the practicability of the TAM in researching individuals' usage intention of technological products, such as consumer adoption of mobile application in the sharing economy (Min, So, & Jeong, 2019), and citizens' acceptance of urban technologies in developing smart cities (Sepasgozar, Hawken, Sargolzaei, & Foroozanfa, 2019). This research adopted TAM to predict and explain tourists' behavioral intention. The TAM was originally developed in the subject of information system. Currently, TAM is extensively applied to the study of tourism in many aspects, including online booking behavior and mobile paying behavior (Zhong, et al., 2022). They have been extensively applied in assessing the

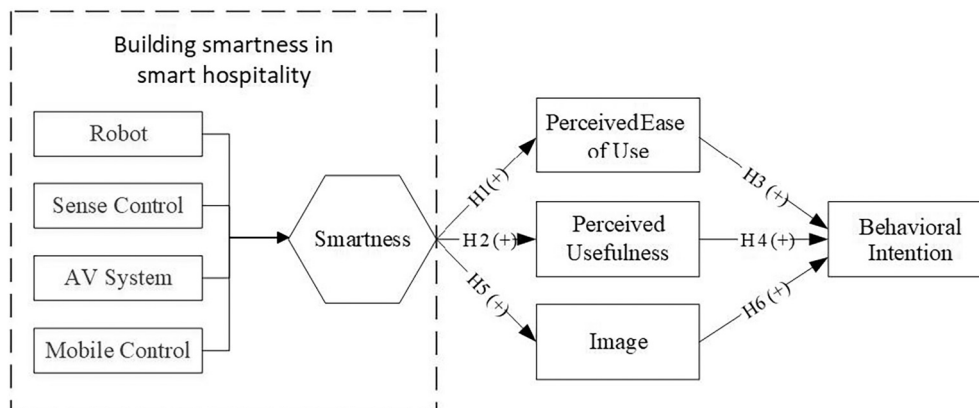


Fig. 1. Conceptual framework.

adoption of innovative technology, service or product.

Smartness is composed of smart technologies and influences tourists' experience. Tourists' cognition and emotions related to smart devices further affect decision-making process (Kals & Maes, 2002; Stottler, 2018). For instance, tourists can find the latest information about intended smart hospitality on online travel platforms, and their decisions are affected by ratings and reviews related to smartness (Del Vecchio, Mele, Ndou, & Secundo, 2018). Robots in the hotels can provide tourists with clear introductions and detail guidance for tourism cities (Kuo, Chen, & Tseng, 2017). Tourists can enjoy a free and comfortable environment that suits their taste and mood (Sarmah, Kamboj, & Rahman, 2017). Guests can select their preferences for mood lighting, room temperature, and entertainment from control panels (Tyagi & Patvekar, 2019). These smart technologies serve guests with reliable and effective manners. Instead of unidirectional technical functions, these novel and attractive technologies also promote guests become co-creators of innovative hotel services (Sarmah et al., 2017). For instance, being served by robots through chatting, guests can enjoy the novel and unique experience. The technical performance (e.g., AI) will also improve and benefit more guests (Choi, Mehraliyev, & Kim, 2020).

Consequently, the following hypotheses are developed:

- H1. : Smartness in smart hospitality has a positive effect on perceived ease of use of smart hotel application.
- H2. : Smartness in smart hospitality has a positive effect on perceived usefulness of smart hotel application.
- H3. : Perceived ease of use of smart hotel application has a positive effect on tourists' behavior intention to visit the smart hospitality.
- H4. : Perceived usefulness of smart hotel application has a positive effect on tourists' behavioral intention to visit the smart hospitality.

### 3.2. Image theory

Image is commonly defined as the sum of individual beliefs, ideas and impressions of a destination (Crompton, 1979). Extensive research on the image concept led to image theory, a descriptive theory of decision-making in which information is represented as image by decision makers (Beach & Mitchell, 1987). Since a growing body of research acknowledges the importance of analyzing individuals' subjective perception and consequent behavior, tourism destination image is believed to reveal tourists' preference intention for tourism characteristics, such as urban styles, entertainment facilities, restaurants, and hospitality (Gallarza, Saura, & Garcia, 2002).

Hence, image acts as a bridge between destination attributes and tourists' behavioral intention. Overall image is composed of tourists' cognitive images of various attributes of a destination and influences tourists' decision to visit (Liu, Ting, & Ringle, 2022). A successful hotel image is not only an identity but also represents a good reputation and high perceived value, which can lead customers to differentiate hotels in the marketplaces (Lai, 2019). Green hotels with eco-friendly programs, for instance, present an image of sustainability and motivate tourists to perform a purchasing behavior (Lee, Hsu, Han, & Kim, 2010). Durna, Dedeoglu, and Balikcioglu (2015) found that overall image can positively affect tourists' revisit intention.

In terms of smartness, smart hotels have an ability to respond to and meet the demands from current guests for "high technology, instant feedback and efficient check-in processing". Smart hotels enhance the competitiveness of millennial visitors who have enough experiences and expectation of smart phones and digital solutions. Attractiveness, dependability and perspicuity make the hotel become a fashion or attractive destination (Yu, Cheah, & Liu, 2022). Instead of using experience based on one technology, smartness establishes smart hotel as a modern destination image.

Accordingly, the following hypotheses are proposed:

- H5. : Smartness in smart hospitality has a positive effect on overall image of smart hotel application.
- H6. : Overall image of smart hotel application has a positive effect on tourists' behavioral intention to visit the smart hospitality.

### 3.3. Conceptual model

Smart technologies are essential components of smartness and can provide smart services to customers, which enhance customers' experiences. Combined with TAM and image theory, Fig. 1 provides the conceptual framework to explain the smartness and hypothesized relationships.

## 4. Research methods

### 4.1. Survey questionnaire

A three-part self-administered survey was employed in this study. Items in the survey questionnaire were adopted from previous studies (as shown in Table 1). The original measures from previous studies were translated into Chinese. Then, a pilot test was conducted among hotel clients, 115 pilot-test questionnaires were completed. In addition, following Brislin (1970), a reverse translation of the revised questionnaire (Chinese edition) was conducted. The questionnaire was compared with the first translation to remove the artificial translation biases of the Chinese questionnaire.

The first part of the questionnaire aimed to gather user experience information about antecedents of smartness and was constructed to measure four major smartness elements: robots, scene control system, AV system and mobile control system. They were measured with attractiveness, perspicuity, efficiency, dependability, stimulation and novelty (Hinderks, Schrepp, Mayo, Escalona, & Thomaschewski, 2019; Laugwitz, Held, & Schrepp, 2008). The second part of the questionnaire was designed to obtain information about effects of smartness on image,

**Table 1**  
Research instrument.

Variables	Measure
1. Smartness (Hinderks et al., 2019, Laugwitz et al., 2008)	The [...] is attractive. The [...] is transparent. The [...] is efficient. The [...] is dependable. The [...] is stimulating. The [...] is novel. <i>These six questions are asked in turn for robots, scene control, AV system and mobile control.</i>
2. Perceived ease of use (Chung et al., 2015)	The interaction with the smart hotel applications is clear and understandable. The interaction with the smart hotel applications does not require much effort. I find the smart hotel applications easy to use. I find it easy to access the desired information through the smart hotel applications.
3. Perceived usefulness (Chung et al., 2015)	The smart hotel applications make the tour useful. The use of smart hotel applications is an effective way to travel in Macau. I use the smart hotel applications to get better access to information in Macau. Overall, I find using the smart hotel applications is useful.
4. Image (Huh et al., 2009)	My overall image of smart hospitality staying is My overall image of smart hospitality is Overall, I have a good image about spending a night(s) at smart hospitality.
5. Behavior intention (Huh et al., 2009)	I am willing to stay at smart hospitality when traveling. I plan to stay at smart hospitality when traveling. I will make an effort to stay at smart hospitality when traveling.



perceived usefulness, perceived ease of use and behavioral intention (Chung, Han, & Joun, 2015; Huh, Kim, & Law, 2009). The last part covered respondents' sociodemographic characteristics.

#### 4.2. Data collection

This study was implemented in an upscale chain hotel in Macau. The hotel provides a robot in the lobby to deliver toothbrushes, razors and other items requested by customers. Customers can use mobile devices to control elevators, doors of guest rooms and AV systems of guest rooms. A scene control system is also provided to change the status of the lighting, curtains, air conditioning and sound system with one button. The population was considered to be all customers over the age of 18 years. The sample (respondents) was selected using a systematic sampling technique. We send a questionnaire to every ten guests. In total, 530 questionnaires were distributed by providing a ten-dollar HKD discount for respondents. During the data preparation stage, we deleted respondents whose survey duration was <150 s, and respondents with the same answers. The final sample consisted of 348 respondents. The demographic profile of the respondents is summarized in Table 2.

### 5. Findings

#### 5.1. Measurement model

The starting point of model assessment is to conduct a composite factor analysis and tests of model fit. The analysis, conducted using ADANCO 2.2.1, began with an assessment of model fit. PLS path-modeling tests of model fit depend on bootstrapping to distinguish between well-fitting and ill-fitting models (Liu, Schubert, Liu, & Henseler, 2022). Hence, ADANCO 2.2.1 with 5000 bootstrap samples and 97.5% confidence interval was adopted to verify model fit. The criterion of the model fit employed for PLS path modeling is the standardized root mean square residual. Though the value of  $d_G$  (0.7096) and  $d_{ULS}$  value (1.0528) do not fall into the corresponding 99% confidence interval, the  $HI99$  of SRMR (0.0266) < 0.05 indicates an acceptable fit.

In addition to measurement model fit, acceptable levels of reliability and validity are conditions for good fit of the structure model. First, according to Müller, Schubert, and Henseler (2018), Dijkstra-Henseler's  $\rho_A$  (Dijkstra & Henseler, 2015) is the most important reliability measurement for PLS. The results of the analysis in Table 3 show that the  $\rho_A$  values of the factors were higher than 0.7, which indicated that the internal consistency reliability was sufficiently high to be accepted. Second, we tested the validity of the model using convergent validity and discriminant validity. The average variance extracted (AVE) is a domain measure of convergent validity (Table 3). In our model, all the AVE scores clearly exceeded the 0.5 recommended threshold,

**Table 2**  
Respondents' profiles.

Measure	Items	Frequency	Percent (%)
Gender	Male	156	44.83%
	Female	192	55.17%
Age	18–30	74	21.26%
	31–40	125	35.92%
	41–50	80	22.99%
	51–60	44	12.64%
	>60	25	7.18%
Education	Senior high school or below	125	35.92%
	University	179	51.44%
	Master's	37	10.63%
	Doctorate	7	2.01%
Visiting times	1	93	26.72%
	2	64	18.39%
	3	60	17.24%
	4	25	7.18%
	>4	106	30.46%

suggesting evidence of good convergent validity. Accurate measurement of discriminant validity was obtained by implementing the index heterotrait-monotrait ratio of correlations (HTMT). As shown in Table 3, all of the HTMT values were smaller than 0.9 and significantly smaller than one, and almost all of the HTMT values were even smaller than 0.85, which means that we can clearly discriminate between factors. Moreover, indicator loading was greater than its cross-loadings, indicating that each indicator was correctly assigned to the right factor (Appendix A). Overall, this measurement model posed no problems for the use of PLS path modeling to develop this study's concept model.

#### 5.2. Intermediate model

In our conceptual model, smartness is a composite with four elements and each element is measured by six indicators. This means that we have a second-order construct, which is modeled and assessed accordingly (Van Riel, Henseler, Kemény, & Sasovova, 2017). Hence, confirmatory composite analysis (CCA, (Henseler & Schubert, 2020)) is the statistical workhorse to validate the concept-driven model. The magnitude of indicator weights and their significance can interpret how the indicators make up the composite and whether all indicators contribute significantly. The indicator weights in Table 4 had the expected signs. It is obvious that the greatest contributors to smartness are AV systems and scene control. Their weights in the composition of smartness are 0.5006 and 0.2283, respectively.

Although the variance inflation factor (VIF) of the indicators was much higher than one, the values were all smaller than 5, which means there was no multicollinearity (Hair, Ringle, & Sarstedt, 2011). Meanwhile, a VIF of 5 can be considered free of common method bias when using factor-based PLS-SEM algorithms (Kock, 2015; Kock & Lynn, 2012). To further examine the validity of the intermediate model, we employed CCA, which aims to test the composite model and can be used to assess overall model fit (Schubert, Henseler, & Dijkstra, 2018). The SRMR value was 0.0337, lower than 0.08, which means that the overall model fit of the composite model was good. Given this, the intermediate model was deemed to be of sufficient quality.

#### 5.3. Structural model

Since the measurement model was of sufficient quality, the analysis continued with the assessment of the structural model. Fig. 2 and Table 4 showed the results of the structural model. The analysis showed that smartness positively, directly and significantly affected perceived ease of use (the bootstrap confidence interval did not include the value of zero;  $f^2 = 4.0329 > 0.35$ ); thus, hypothesis 1 was supported. Furthermore, smartness positively and insignificantly affected perceived usefulness (the bootstrap confidence interval included the value of zero;  $f^2 = 0.0239$  is just slightly larger than 0.02), hypothesis 2 was not supported.

Perceived ease of use negatively and insignificantly affected tourists' behavioral intention (the bootstrap confidence interval included the value of zero; effect size  $f^2 = 0 < 0.02$ ); therefore, hypothesis 3 was not supported. Perceived usefulness positively, directly and significantly affected tourists' behavioral intention (bootstrap confidence interval did not include the value of zero;  $f^2 = 0.0822 > 0.02$ ); therefore, hypothesis 4 was supported. Moreover, perceived ease of use directly and significantly affected perceived usefulness, and. Perceived usefulness played the role of the mediator. This indicated that tourists were more concerned about whether smart devices were useful than whether they were easy to operate.

Smartness positively, directly and significantly affected overall image (bootstrap confidence interval did not include the value of zero;  $f^2 = 2.9057 > 0.35$ ); therefore, hypothesis 5 was supported. Overall image positively, directly and significantly affected tourists' behavioral intention (bootstrap confidence interval did not include the value of zero;  $f^2 = 0.3706 > 0.35$ ); thus, hypothesis 6 was supported.

**Table 3**  
Assessment results of the measurement model and intermediate model.

Construct	Reliability ( $\rho_A$ )	Smartness (composite)	Perceived ease of use	Perceived usefulness	Image	Behavioral intention
Smartness (composite)	0.9710	0.8250				
Perceived ease of use	0.9126	0.8013	<b>0.7222</b>	0.8416	0.7725	0.7220
Perceived usefulness	0.9059	0.7530	0.7072	<b>0.7033</b>	0.8640	0.8283
Image	0.9214	0.7440	0.5961	0.7510	<b>0.7961</b>	0.8650
Behavioral intention	0.9270	0.5971	0.5208	0.6884	0.7484	<b>0.8087</b>

Notes: The values below the diagonal represent the squared correlations; the values upper the diagonal represent HTMT; the values (in bold) in the diagonal represent AVE.

**Table 4**  
Bootstrap results of conceptual model.

Hypothesized path	Beta	Mean	Standard error	t-value	p-value	Percentile bootstrap quantiles		Hypothesis supported
						0.25%	99.75%	
H1: Smartness→PEOU	0.8952	0.8947	0.0207	43.1742	0.0000	0.8471	0.9303	Yes
H2: Smartness→PU	0.1807	0.1797	0.1222	1.4791	0.1394	-0.0487	0.4094	No
H3: PEOU→BI	-0.0051	0.0008	0.0841	-0.0601	0.9521	-0.1664	0.1550	No
H4: PU → BI	0.3248	0.3171	0.1275	2.5481	0.0110	0.0720	0.5751	Yes
H5: Smartness→Image	0.8625	0.8622	0.0278	31.0344	0.0000	0.8004	0.9098	Yes
H6: Image→BI	0.5875	0.5891	0.0979	5.9987	0.0000	0.4043	0.7887	Yes

Notes: "PEOU" represents perceived ease of use; "PU" represents perceived usefulness; "BI" represents behavioral intention.

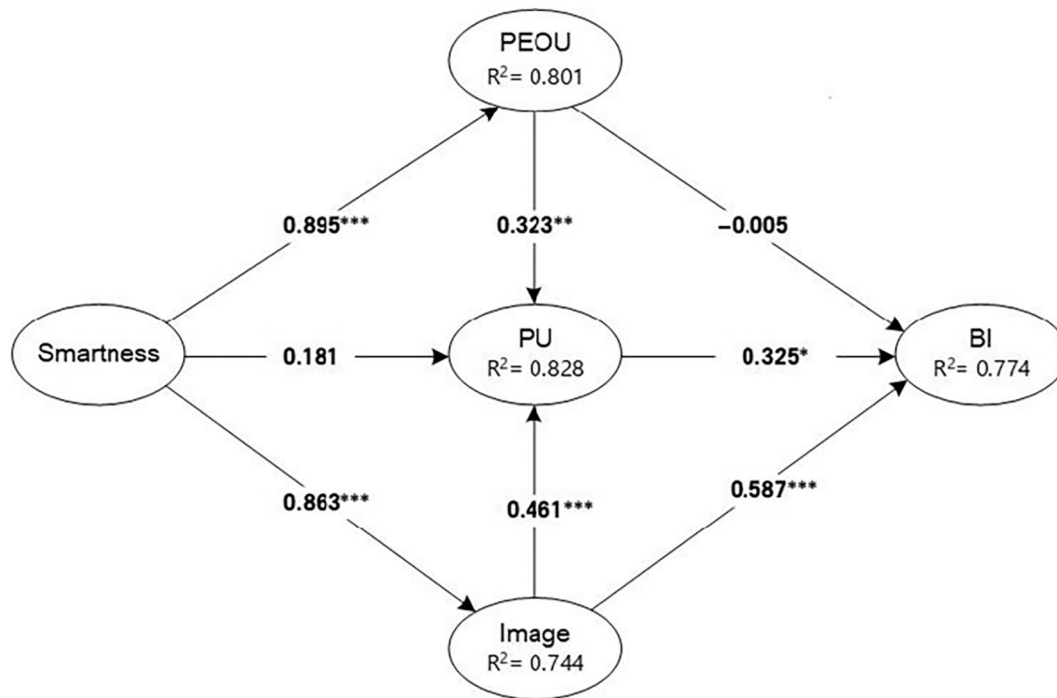


Fig. 2. Structural modeling results of conceptual model.

In addition, perceived ease of use positively, directly and significantly affected perceived usefulness (the bootstrap confidence interval (0.0395, 0.5869) did not include the value of zero;  $f^2 = 0.1207$  is close to 0.15). Image positively, directly and significantly affected perceived usefulness (the bootstrap confidence interval (0.2624, 0.7357) did not include the value of zero;  $f^2 = 0.3173$  is close to 0.35). These results indicate that smartness positively and indirectly affected perceived usefulness through perceived ease of use and image. Perceived ease of use and image are mediators for the relationship between smartness and perceived usefulness (Nitzl, Roldan, & Cepeda, 2016).

The value of  $R^2$  was 0.801 for perceived ease of use, suggesting that 80.1% of the variance in perceived ease of use was attributed to smartness. Approximately 82.8% of the variance in perceived usefulness

could be attributable to smartness, perceived ease of use and overall image. A total of 74.4% of the variance in the overall image was attributed to smartness. Finally, 77.4% of the variance in tourists' behavioral intention was attributable to perceived ease of use, perceived usefulness and overall image.

5.4. Competing models

The conceptual model in this study is an integrated model that combines TAM and image theory. Fig. 3 illustrates the structural model of the TAM. The results were similar to the empirical analysis of the integrated model. Hypotheses 1, 2 and 4 were accepted, and hypothesis 3 was not supported. Fig. 4 shows the structural model of image theory.

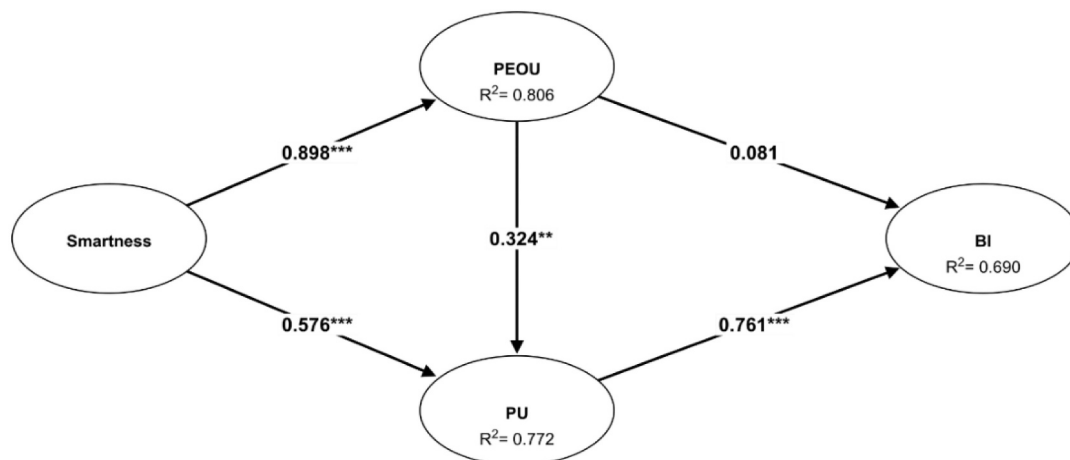


Fig. 3. Partial model based on the technology acceptance model.

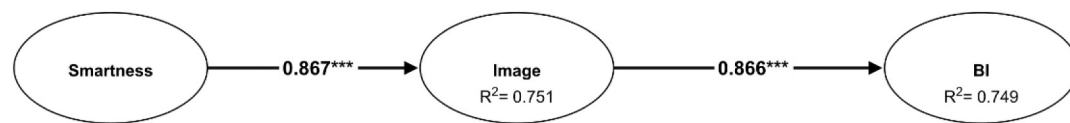


Fig. 4. Partial model based on image theory.

The results supported hypotheses 5 and 6, which is consistent with the integrated model.

Table 5 shows the degrees of impact of smartness on tourists' behavioral intention in the integrated model, the TAM model, the image theory model and no theory. It is obvious that the integrated model explains the effect of smartness more comprehensively than any model based on a single theory or no theory. Image theory explains more of the impact of smartness than the TAM theory. Consequently, the integrated model employed in this study had a better level of predictive explanatory power.

Since in spite of a high inter-construct correlation, smartness does not have a direct effect on behavioral intention, we engage in mediation analysis (Henseler, 2020). Mediation analysis can help explain how the exogenous variable smartness finally impacts behavioral intention. The conceptual model in this study is an integrated model that combines TAM and image theory. By means of mediation analysis, we can figure out to what extent the theories contribute to explaining behavioral intention.

Table 6 shows the indirect effects made up of significant direct effects and assigns them to TAM, image theory, and a combination of both. As the variance accounted for (VAF) reveals, the indirect effect of Smartness on Behavioral Intention via Image plays a dominant role, whereas the other two indirect effects are substantially smaller. The effectiveness of smartness serves thus primarily as image generator and only secondarily a tool that creates usefulness.

Table 5  
Effect of smartness on behavioral intention in the three models.

Models	adjusted R <sup>2</sup>	total effect of smartness on BI
Integrated Model	0.7721	0.7841
TAM	0.6881	0.7329
Image Theory	0.7487	0.7503
No theory (effect of smartness on BI directly)	-	0.5971

Table 6  
Mediation analysis: Indirect effects of smartness on behavioral intention.

Theory	Indirect effect	Value	VAF
TAM	Smartness - > Perc. Ease of Use - > Perc. Usefulness - > Behavioral Intention	0.0940	13%
Image Theory	Smartness - > Image - > Behavioral Intention	0.5066	69%
Combination	Smartness - > Image - > Perc. Usefulness - > Behavioral Intention	0.1293	18%

## 6. Discussion

Although smart hospitality is a popular topic in the tourism and hospitality industry, there is still a lack of understanding of the relationship between smartness and tourists' behavioral intention. The main purpose of this study was to explore how smartness is composed and how smartness influences tourists' behavioral intention. We proposed a conceptual framework of tourists' behavioral intention based the TAM and image theory, which explains their relationships with dimensions of smartness, perceived ease of use, perceived usefulness and image. The model was tested with data from tourists who stayed in smart hospitality in Macau.

This study regards four popular smart devices (i.e., robots, scene control, AV systems and mobile control) as indicators of smartness in smart hospitality. The findings show that smart devices play an indispensable role in smartness. AV systems and scene control are especially attractive and representative of smartness for tourists. These results are consistent with the proposition of Buhalis et al. (2019) that IoT and automatic devices enhance tourists' enjoyment and self-service experience.

However, smartness doesn't have direct effect on behavioral intention. Perceived ease of use, perceived usefulness and image play mediating roles in the relationship between smartness and behavioral intention. Image of smartness as intrinsic motivation accounts for a more important part in influencing behavioral intention, even has a mediating effect on positive relationship between smartness and perceived usefulness (Li & Chen, 2019).

The results reveal that smartness has a strongly significant effect on perceived ease of use (hypothesis 1) but has an indirectly positive effect on perceived usefulness via perceived ease of use (hypothesis 2). The reason for this discrepancy is that perceived ease of use is an antecedent of perceived usefulness (Chung et al., 2015). Tourists think a special technology is useful only when it can improve efficiency and performance, and perceived ease of use refers to how much effort they can save (Davis, Bagozzi, & Warshaw, 1989). Then, perceived ease of use leads to behavioral intention to visit smart hospitality through perceived usefulness (hypothesis 3, hypothesis 4). Perceived ease of use indicates tourists' feelings about smart devices' attributes, while practical usefulness indicates benefit and value. Pradhan et al. (2018) verified that tourists will not consume special attributes with no value but will consume things that are both easy to use and valuable.

In addition, smartness can produce a better image to tourists, which leads to tourists' willingness to stay in smart hospitality. The results suggest that smartness has a strong significant impact on overall image (hypothesis 5). Smart devices contribute to a "smartness" image in hospitality. Tourists recognize the smartness of hospitality if it is equipped with high-tech products. They can also verify this impression when they interact with robots and enjoy smart services. At the same time, participating in the "smartness" image can produce emotional value and demonstrate identity value for tourists when they share these experiences with others (Kabadayi et al., 2019). Thus, overall image of smart hospitality directly and significantly affects tourists' behavioral intention (hypothesis 6). Our findings are consistent with the propositions that image of smart hospitality can influence tourists' decision-making process (Yadav, Dokania, & Pathak, 2016).

## 7. Conclusions

### 7.1. Theoretical implications

This study provides numbers of theoretical implications in the field of technological change research.

First, this research contributes to the concept of "smartness" by building a composite model. The composite model transforms figurative objects (i.e., smart devices and smart systems) that tourists touch into abstract feelings that tourists perceive (i.e., smartness). Prior studies discussed the design issues and effect of smart technology but ignore the generated overall feeling through all technologies. Although smart technologies are effective, the smart hospitality transfer is uncertain and operationally complex. These characteristics make the measurement and assessment of smart hospitality be difficult (Damanpour, 2014). This study contributes to distinguishing technologies and artifact through PLS-PM with composite and common factor models.

Second, this study contributes to smart hospitality research by extending the TAM from users to tourists. The original TAM focuses on the usage of software and computer technology (Davis et al., 1989). At that time, computer and relevant technologies are business tools, instead of a fashion for tourists. Apart from smart technology adoption, this study focused on the overall image and intention generated from smartness. In a smart hotel, some guests may refuse to use the robots or mobile control application, but they can also feel the high-tech atmosphere of the hotel. This study extends the TAM for both users and non-users of smart hospitality.

Third, this study contributes to explore the effects of smartness on behavioral intention through both value and image. To the best of our knowledge, no study has explored the concept of smartness and the relationship between smartness and tourists' behavioral intention using the TAM theory and image theory. Incorporating image into the analysis brings a more comprehensive view of smartness.

Fourth, our study provides a paradigm for designing technical artifacts using composite factors and PLS-PM in technological change research (Müller et al., 2018). PLS path modeling is a multivariate statistical method with growing popularity in tourism and hospitality

research (Ali, Rasoolimanesh, Sarstedt, Ringle, & Ryu, 2018). The research findings verify the usefulness of the composite model with PLS-PM, which means that PLS-PM is a favorable method for confirmatory research to address latent variables and artifacts (Henseler, Müller, & Schubert, 2018).

Furthermore, this study proposed an integrated model combining TAM and image theory, which addresses some gaps in the literature regarding the analysis of tourists' visiting intentions about smart hospitality. As suggested in our study, perceived usefulness and image are important drivers of tourists' intention. Tourists pay attention not only to the practical value of smart devices in smart hospitality, but also to the emotional value and identity value produced by the overall image of smartness. Therefore, this model can help improve and strengthen future research by offering a new perspective in the context of smart hospitality. The findings also provide an orientation for scholars who are committed to designing smart hospitality.

### 7.2. Practical implications

Our findings contribute to several practical implications and can be summarized into three areas. First, managers of smart hospitality can consider providing tourists with smart services that are practical and easy to use. This study sheds light on how to define smartness and notes that smart devices and smart systems are essential components of smartness. Thus, smart service with smart technologies is a typical sign of smart hospitality that distinguishes from other hotels. However, tourists use smart services only if they are easy to operate, and they are willing to pay for useful smart services. Hence, managers should consider the economic benefits of smart services when designing smart systems.

Second, it is a wise strategy for smart hospitality to create a smartness image from a public view. Hotels can display novel and familiar smart devices in lobbies that tourists have the opportunity to experience. For example, tourists can use augmented reality (AR) applications to obtain city information and better understand the current environment (Tom Dieck & Jung, 2018). Managers can design hotel websites with high-tech videos showing smart services in hotel rooms and create a community for people to share experiences or consult. The visual design of websites may not only establish a smartness image for hotels but also improve website esthetics and emotional appeal, which can result in tourists' positive attitude toward smart hospitality (Cyr, Head, Lim, & Stibe, 2018).

Third, this research provides a reference for promoting smart tourism. Accommodation plays a critical role in tourism, and understanding tourists' intention to use smart hospitality is helpful for sustainable smart tourism (Pradhan et al., 2018). In addition, smart tourism collects and analyzes data derived from physical infrastructures and information technologies. The results of this study can help smart hospitality improve business strategies to attract more tourists, which in turn will enrich the database of smart tourism.

### 7.3. Limitations and future research

Although our research offers some important insights, this study has several limitations. In our study, smartness was composed of four smart devices that are currently common and popular among millennial generation. However, generation Z (2001- present), known as Digital Natives, who grew up during an era of information and technology development, will be the main target market of hospitality and tourism in the next five to ten years (Setiawan et al., 2018). Hence, future research should investigate smart devices that can represent smartness for the next generation and consider these smart devices when describing the smartness.

Moreover, this study focused on tourists' behavioral intention rather than actual behavior. Although our findings largely predict the tendency of tourists' decision-making, there will still be deviations in actual



behavior (Wang, Wang, Wang, Li, & Zhao, 2018). Thus, future research can collect data on tourists' actual behavior and establish a model to compare tourists' behavioral intention and actual behavior. Finally, this study mainly identifies smartness in the context of smart hospitality. In the future, we will consider the composition of smartness in the context of smart tourism.

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### Data availability

Data will be made available on request.

### Appendix A. Indicator loadings and cross loadings of the measurement model

Variables	Indicator	Smartness	PEOU	PU	Image	Behavioral intention
Perceived Ease of Use (PEOU)	PEOU1	0.7862	<b>0.9072</b>	0.6677	0.6665	0.6116
	PEOU2	0.7673	<b>0.9144</b>	0.6528	0.6295	0.5768
	PEOU3	0.7397	<b>0.9084</b>	0.6918	0.6066	0.5843
	PEOU4	0.6832	<b>0.8272</b>	0.7098	0.6149	0.5890
Perceived Usefulness (PU)	PU1	0.6995	0.6995	<b>0.8680</b>	0.6166	0.6463
	PU2	0.6866	0.6472	<b>0.9008</b>	0.6706	0.6377
	PU3	0.7159	0.6665	<b>0.9082</b>	0.7172	0.6958
	PU4	0.7589	0.6799	<b>0.8519</b>	0.7793	0.6981
Image	Ima1	0.7745	0.6863	0.7415	<b>0.9178</b>	0.6966
	Ima2	0.7667	0.6667	0.7421	<b>0.9570</b>	0.7520
	Ima3	0.7318	0.6211	0.7237	<b>0.9134</b>	0.7806
Behavioral Intention (BI)	BI1	0.7028	0.6186	0.7018	0.7728	<b>0.9172</b>
	BI2	0.6725	0.6303	0.7059	0.7372	<b>0.9499</b>
	BI3	0.6767	0.6101	0.7230	0.7309	<b>0.9353</b>

Notes: The values in bold represent factor loadings.

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