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Is Smart Tourism Technology Important In Predicting Visiting Tourism Destination? Lessons From West Java, Indonesia

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Abstract
This study analyzes tourist behavior in tourist destinations influenced by smart tourism technology and uses the technology acceptance model (TAM) as a model for acceptance of smart tourism technology. This study used a sample of 324 tourists in West Java Province, Indonesia. Partial least square is applied to assess the relationship between smart tourism technology, perceived usefulness, perceived ease-of-use, travel intention, and visiting tourism destinations. The results of this study have revealed that the integration of TAM and smart tourism technology provides a complete explanation of the adoption of smart tourism technology. The results showed that smart tourism technology significantly affected perceived ease of use, perceived usefulness, and attitude. Travel intention was found to be directly influenced by attitude. Then, visiting tourist destinations is influenced by travel intention. By identifying smart tourism technology, various stakeholders, such as the government, tourism service providers, and tourists, can optimize a more comprehensive travel experience through smart tourism technology. This research has developed TAM and integrated it with smart tourism technology to assess tourists' attitudes and behavior in tourist destinations.

Keywords: smart tourism technology, perceived ease of use, perceived usefulness, travel intention, visiting tourism destination

INTRODUCTION

Technological advances have resulted in major changes in the tourism industry. The rapid advancement of information communication technology (ICT) in the context of travel and tourism has significantly influenced industrial operations and the attitudes and behavior of tourists (Ghaderi et al., 2018). Moreover, technology has changed the static and practical aspects of tourism management and marketing into a dynamic process that allows tourism providers, stakeholders, intermediaries, and tourists to develop technology in the tourism industry and is also influenced by it (Sigala, 2018). Thus, technological developments in tourism have helped tourists personalize destination-related activities, making it easier for them to get more travel experiences. In this competitive and challenging environment, various kinds of technology are used in tourism, and currently, the most frequently used is smart tourism technology because it can directly influence the attitudes and behavior of tourists (Jeong & Shin, 2019; Lee et al., 2018; Um & Chung, 2019; Yoo et al., 2017). Thus, developing smart tourism technology based on tourist needs is important to analyze to increase the adoption of smart tourism technology. One of the main research questions is whether adopting smart tourism technology can increase travel intention and visiting tourism destination behavior.

One of the most frequently used models in explaining technology adoption is the technology acceptance model (TAM) (Davis, 1989). The literature on technology adoption in tourism has used TAM, one of the most established and widely accepted models, to explain the phenomenon of technology adoption (Hua et al., 2017; Nunkoo et al., 2016; Xia et al., 2018). However, due to the complexity of the technology adoption process at tourist destinations, scholars (Jeong & Shin, 2019; Kim et al., 2019; Susanto et al., 2020) have recommended continuing systematic efforts to analyze the phenomenon of technology use in tourist destinations.

Previous research has also discussed various kinds of smart technologies in tourism that affect tourist visits (Kim, 2019; Tussyadiah et al., 2017; Xia et al., 2018). Although TAM and smart tourism technology have been analyzed many times before, surprisingly, none of the identified existing studies have tested and integrated smart tourism technology and TAM into a single comprehensive model influencing travel intention and the behavior of visiting tourism destinations. It can be stated that this research focuses on a technology acceptance model for smart tourism technology that has not previously used a similar model. Thus, the need to examine these relationships is clear, as it can offer a better understanding of adopting smart tourism technologies that influence tourist intentions and behavior.

This study explores issues with specific reference to visiting tourism destinations in Indonesia. Tourist destinations in Indonesia were chosen in this study for three reasons. First, the tourism sector in Indonesia is growing both as a result of the increase in the number of tourists and the income in the tourism sector. Based on data from the government of the Republic of Indonesia, the number of foreign tourist arrivals in 2018 was 15.81 million, with an upward trend of 12.58% from the previous year. Nationally, the tourism sector can generate a Gross Domestic Product of US $ 19.29 billion, equivalent to 4.8% of Indonesia's total GDP (BPS-Statistics Indonesia, 2019). Second, in most developing and developed countries, technology in the tourism industry is widely adopted, affecting tourist visits (Ghaderi et al., 2018; Hua et al., 2017; Jeong & Shin, 2019; Shafiee et al., 2019). Third, based on data from the World Tourism Organization (WTO), international tourist arrivals around the world grew by 4% in 2019, with a total of 1.5 billion, and countries in Southeast Asia, including Indonesia, recorded a growth of around 8% (UNWTO, 2020).

This study presents an integration model of TAM and smart tourism technology to fill these gaps. This is because visiting tourist destinations are a critical aspect of tourist behavior which seems to be influenced by smart tourism technology and technology adoption. Thus, this study aims to explore and explain these influences, then test the hypotheses informed by TAM. The research continues with a literature review, including some background information on smart tourism technology and TAM, followed by a research framework and developing hypotheses. Then, it describes the methodology and research findings before discussing the implications and limitations of the study.

LITERATURE REVIEW

Smart tourism technology

Smart tourism technology literature can be classified into three major themes: the role of smart tourism technology in the tourism industry, the features and characteristics of smart tourism technology, and the adoption of smart tourism technology in the tourism industry (Yoo et al., 2017). First, in the role of smart tourism technology in the tourism industry, technology has been combined with tourism, and tourist destinations have become more competitive, offering benefits to everyone involved in tourism (Buhalis, 1997). Tourism with smartphone devices and sensors is useful before, during, and after a tour (Buhalis & Amaranggana, 2015). In addition, the impact of smart technology has been highlighted recently, and tourists are looking for suitable facilities and services that will help enhance their travel experience (Ghaderi et al., 2018). This shows that smart tourism technology plays an important role in changing the tourism industry, making destinations more competitive, providing convenience for tourists, and improving the travel experience. Second, regarding the features and characteristics of smart tourism technology, the previous study analyzed tourist preferences for technology in the tourist attraction (Wang et al., 2016), smart tourism technology (Susanto et al., 2020), technological utilities (Ballina et al., 2019) and smart tourism destination instruments and platforms (Başer et al., 2019). These studies discuss the technology and smart features used by tourists in traveling. The previous study used more detailed dimensions of smart tourism technology, such as smart information systems, intelligent tourism management, smart sightseeing, e-commerce systems, smart safety, intelligent traffic, smart forecast, and virtual tourist attraction (Susanto et al., 2020). Building on these studies, this study uses the dimensions of smart tourism technology because these dimensions are found in tourist destinations in West Java, Indonesia. Third, the adoption of smart tourism technology, previous research analyzed the adoption of smart tourism technology which affects tourists 'experience and psychological behavior (Jeong & Shin, 2019), tourists' happiness (Lee et al., 2018), tourist satisfaction (Um & Chung, 2019), and selecting and visiting tourism destination (Ghaderi et al., 2018). These studies have shown that adopting smart tourism technology can affect tourists' attitudes and behavior. Complementing these studies, this study provides an understanding of how smart tourism technology enhances usefulness and ease of use will affect travel intention in visiting tourist destinations.

According to Gretzel et al. (2015), this trend is known as smart tourism. The word "smart" became popular due to the use of smartphones and has since been applied in many fields, which can be divided into devices and spaces. Smartphones, smart cars, and smart tags are examples of such usage. "Smart" refers to intelligent, combined, digital, massive, wireless, etc. (Um & Chung, 2019). In practice, smart technology enables real-time and targeted communication between citizens-citizens, citizens-visitors, and visitors-visitors across synchronized technological environments (Buhalis & Amaranggana, 2015). Several previous studies have discussed the use of smart technology in tourism, such as smart tourist attractions (Susanto et al., 2020; Wang et al., 2016), travel mobile applications (Im & Hancer, 2016), mobile tour information services (Kim et al., 2019), and smart tourism technology (Lee et al., 2018; Um & Chung, 2019). Many studies on tourism and technology have been conducted, and efforts have been made to define them and understand their attributes (Gretzel et al., 2015; Wang et al., 2013). In complementing previous studies, this study discusses the adoption of smart tourism technology, which affects tourists' intentions and behavior.

Technology Acceptance Model

The TAM is widely applied to explain the behavioral use of information technology. The TAM (Davis, 1989) comes from the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975). The original TAM proposes perceived ease of use and perceived usefulness as beliefs about technology that affect individual attitudes toward using these technologies (Davis, 1985). The TAM model assumes that a person's perception of usability and ease of use are the two main factors influencing one's adoption of a technology (Agag & El-Masry, 2016). Perceived usefulness is 'the extent to which a person believes that using a particular system will improve his job performance' (Davis, 1989). Perceived ease of use is 'the extent to which a person believes that using a particular system will free the user from effort' (Davis, 1989). Davis has focused on TAM from both an individual and an organizational perspective. TAM has also been used to assess the extent to which new technologies are adopted. TAM is also used in tourism (Im & Hancer, 2016; Sahli & Legohérel, 2015). The current study focuses on applying TAM to investigate the use of smart tourism technology as a predictor in making travel decisions and visiting tourism destinations.

Three factors make TAM a popular model for explaining technology adoption. First, this model provides reliable results to predict and explain user acceptance of various technologies in many organizational and cultural contexts (Jamshidi & Hussin, 2016). Second, TAM is developed from a strong theoretical basis (reasoned action model and planned behavior model) and, due to intense testing in various industries, offers an inventory of measurement scales, which makes it operationally attractive (Chuttur, 2009; Jamshidi & Hussin, 2016). Third, several studies have also found that TAM can be applied in predicting various technologies (Lee et al., 2012; Suhartanto & Leo, 2018). Due to its popularity, many studies have been conducted, adding more predictors in the next TAM model testing. Scholars have also validated TAM as a strong and parsimonious framework for understanding user acceptance of technology in various contexts, including tourism (Hua et al., 2017; Nunkoo et al., 2016; Tussyadiah et al., 2017; Xia et al., 2018). For this reason, this study uses TAM as the main model for adopting smart tourism technology.

Travelers' attitude

TAM was founded based on TRA, which justifies the influence of attitudes on individual behavior. TAM considers attitude as a result of perceived usefulness and perceived ease of use (Davis, 1989). According to Ajzen and Madden (1986), attitude can be considered as an individual's mental response to a positive or negative stimulus. Attitudes and behavioral intentions of users towards new technology or systems have been described and predicted by TAM (Legris et al., 2003). According to Huang et al. (2009), the relationship between attitude and behavioral intention to use social media has a significant effect when seeking travel information from tourists. Several previous studies have also confirmed the effect of attitude on travel intention (Chung et al., 2015; French et al., 2017; Ghaderi et al., 2018). Thus, these studies show an effect of attitude on intention. Tourists who have a positive attitude towards smart tourism technology will use it in traveling. Ghaderi et al. (2018) proved the effect of tourist attitudes on travel intention in smart destinations in Isfahan, Iran. In line with these findings, Chung et al. (2015) proved the effect of attitude on augmented reality on destination visit intention. These studies show the effect of attitude on visit intention. Thus, the following hypothesis is developed:

H1. Attitude significantly influences travel intention.

Perceived usefulness and perceived ease of use

There are several constructs in TAM, originally introduced by (Davis, 1989); TAM describes technology adoption through the constructs of attitudes, perceived usefulness, perceived ease of use, and intention. The TAM model assumes that perceived usefulness and ease of use are the two main factors influencing technology adoption (Agag & El-Masry, 2016). Perceived ease of use and perceived usefulness are why people use certain technologies. Furthermore, most previous studies highlighted that perceived usefulness and ease of use are the main reasons for technology adoption (Agag & El-Masry, 2016; Priya et al., 2018). More focused on tourism, a large number of previous studies have explained the relationship between perceived usefulness and perceived ease of use towards attitude in the scope of information systems and technology applications in the tourism industry (Hua et al., 2017; Im & Hancer, 2016; Sahli & Legohérel, 2015). Smart tourism technology that is easy to use and useful for tourists in any tourism process will affect their attitude towards using this technology. For this reason, this study uses two main adoption factors for TAM, perceived usefulness and perceived ease of use, in influencing attitude. Thus, the following hypotheses are proposed:

H2. Perceived usefulness significantly influences attitude.

H3. Perceived ease of use significantly influences attitude.

Travel intention

TAM is an original theory about predicting behavior in an individual's intention to perform a certain behavior determined by the attitude towards the behavior (Davis, 1989). The intention has been used to predict various behaviors, including consumer and travel decisions. The difference between intention and behavior is the 'intention-behavior gap" (Sheeran, 2002). High intention to perform a behavior strongly predicts implementing that particular behavior (Ajzen, 1991). Due to difficulties in predicting generic decision-making behavior, it is important to gain insight into the gap between intention and behavior (Kah et al., 2016). In the context of the behavior of visiting tourist destinations (Ghaderi et al., 2018), research shows a relationship between travel intention to selection and visiting tourist destinations. If prospective travelers desire to visit a destination, they will try to visit it (Koo et al., 2016). This shows a relationship between travel intention and visiting tourism destination behavior. Thus, the hypothesis for this relationship is:

H4. Travel intention significantly influences visiting tourism destinations.

Smart tourism technology and TAM

Technological factors in this study were used as external variables to determine the user's cognitive beliefs, in particular, perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989). Previous research has validated various external variables related to technology that directly influence two constructs in the TAM model: perceived usefulness and usefulness in tourism, such as social media (Hua et al., 2017) and smartphone apps. (Xia et al., 2018), features of internet services (Lin et al., 2010), technology experience (Kim et al., 2008), and travel mobile apps. (Im & Hancer, 2016). Kim et al. (2010) suggest that integrating individual differences and system design features is very important and useful for exploring the interaction between humans and mobile devices. Kim and Qu (2014) argue that previous research recognizes external variables as determining factors for analyzing user acceptance of new ICTs, and a large number of external variables have been verified and extended from TAM while focusing on the main constructs of TAM (perceived usefulness and perceived ease of use). It is noteworthy that a large number of previous studies explain the relationship between usefulness and attitudes in information systems and technology applications (Hua et al., 2017; Im & Hancer, 2016; Sahli & Legohérel, 2015). In the context of smart tourism, this study analyzes smart tourism technology as an important antecedent of perceived usefulness and perceived ease of use, and the following hypotheses are proposed:

H5. Smart tourism technology significantly influences perceived usefulness.

H6. Smart tourism technology significantly influences perceived ease of use.

TAM argues that people tend to have favorable attitudes and behavioral intentions when new systems or technologies are easier to use and are expected to improve performance (Venkatesh, 2000). There is a fundamental difference between tourist attractions that adopt more technology with other tourist attractions, such as having a smart information system, intelligent tourism management, smart sightseeing, e-commerce system, smart safety, intelligent traffic, smart forecasting, and virtual tourist attractions at smart tourist attractions (Wang et al., 2016). Then, technologies such as smart devices, tourism-related platforms, and ICTs can influence the tourism experience from the planning stage to after the tour (Buhalis & Amaranggana, 2015). Therefore, a smart system encourages visitors to explore the city better and improve their travel service experience through direct feedback from a smart tourism technology system (Gretzel et al., 2015). Many studies have examined the use of smart tourism technology (Shafiee et al., 2019; Um & Chung, 2019) that will affect travel intention (Chung et al., 2015; Ghaderi et al., 2018; Jeong & Shin, 2019). This shows that technology is one of the considerations for tourists in traveling. Thus, smart tourism technology will affect travel intention. Then the proposed hypothesis is as follows:

H7. Smart tourism technology significantly influences travel intention.

Although the construct of smart tourism technology appears to be a different technical problem, the important point is how tourist attractions design a "value proposition" related to the development of smart tourism technology. Tourist behavior is driven by the development of smart technology, such as accessing more information via the Internet, asking for better services, wanting more specific offers, being more knowledgeable, mobile, critical, and price sensitive, etc. (Sevrani & Elmazi, 2008). This smart tourism technology enables destinations to be "smart" in terms of generating rich, real-time intelligence about the needs and desires of tourists. The purpose of smart tourism technology is to utilize a system to optimize the tourist experience, increase the effectiveness of resource management, and maximize tourist satisfaction and competitiveness of tourist attractions (Buhalis & Amaranggana, 2015). Several factors influence the behavior of visiting tourist destinations such as a physical contract (Chen et al., 2020), cultural and national characteristics (Filimonau & Perez, 2019), travel experience, photos, videos, and other content shared on social media may influence other prospective tourists in their destination selection decision (Paul et al., 2019). The selection of tourist destinations is an important aspect of tourist behavior influenced by ICT trends (Ghaderi et al., 2018). This study confirms that technology can significantly influence individual behavior in visiting tourist destinations, supported by previous research (Jeong & Shin, 2019; Yoo et al., 2017). The significant impact of technology on the behavior of tourists visiting tourist destinations has motivated the tourism industry to embed technology in tourist destinations (Jeong & Shin, 2019). The convenience provided by tourist destinations due to technology will encourage tourist behavior to visit tourist destinations. Thus, tourist behavior must always be the starting point when designing smart tourism technology. Then the proposed hypothesis:

H8. Smart tourism technology significantly influences visiting tourism destinations.

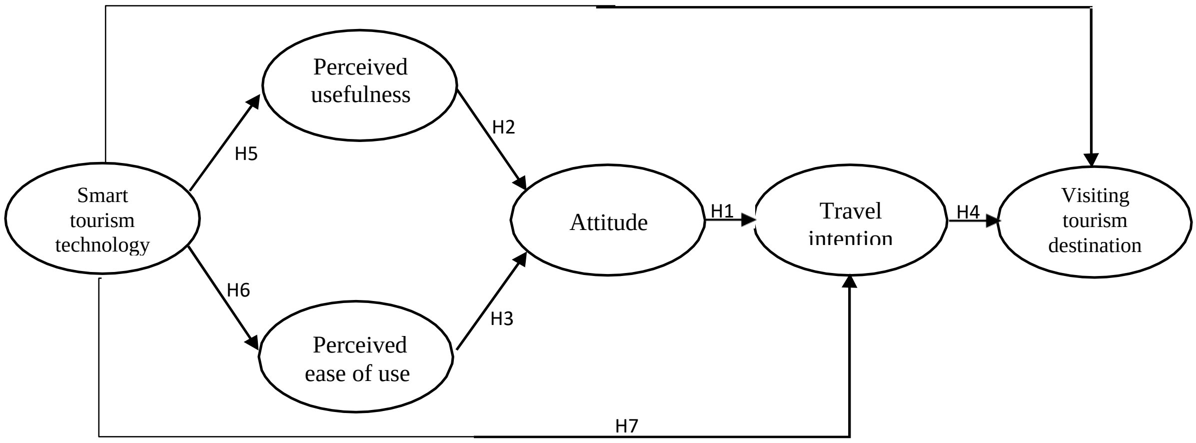


Figure 1. Research Model

METHOD

In this study, we tried to understand the adoption of smart tourism technology by investigating TAM and its impact on visiting tourism destinations. Several previous studies that have analyzed this construct adapted their measurements from the existing literature. Invariable measurement, smart tourism technology is measured using tourist preferences of smart tourist attractions (Wang et al., 2016), smart tourism technology (Susanto et al., 2020), and technological utilities (Ballina et al., 2019). These scales are adopted because their psychometric values are reliable and valid. In addition, this research also focuses on the smart technology instruments used by tourists in traveling. Then, the measurement of perceived usefulness and perceived ease of use which is part of the TAM, is measured by (Kim et al., 2008; Venkatesh, 2000). Measurements of tourist attitude, travel intention, and visiting tourism destinations were modified from previous studies (Ghaderi et al., 2018; Halpenny et al., 2018). This research adjusts to the context of smart tourism technology. Table I displays the constructed instruments.

Primary data was collected using a questionnaire survey. The self-administrated questionnaire was prepared in Indonesian because the respondents were Indonesian tourists. The first part of the questionnaire is a statement of the respondent's willingness to participate in this survey. The second part covers the socio-demographic characteristics of the respondents. The following sections include statements regarding smart tourism technology, perceived usefulness, perceived ease of use, attitude, travel intention, and visiting tourism destinations. All items were measured with a five-point Likert scale, from "strongly disagree (1)" to "strongly agree (5)". Table 1 describes the variables and questionnaire statements based on previous research and revised according to the research context.

A pilot test of 30 tourists was performed to ensure that the questions were unambiguous and that there were no technical errors that might impede data collection. Data were collected from October 2019 to December 2019 with convenience sampling was used to select the sample. Respondents were found in various tourist destinations in West Java Province. Eligible participants were then asked to respond to the questionnaire voluntarily. The samples were taken from domestic Indonesian tourists, and 350 responses were obtained, of which 324 were useful. Considering the proposed model and the research objectives, this study uses structural equation modeling (SEM) to analyze the data. SEM is a technique that allows a researcher to evaluate the validity of a theory (Hair et al., 2017). This study uses the PLS-SEM analysis technique because it is a comprehensive multivariate approach to statistical analysis that can simultaneously test every relationship between variables in the conceptual model, including measurement and structural components (Hair et al., 2017). PLS-SEM is also used when the research objective is to better understand increasing complexity by exploring theoretical extensions of established theories (Hair et al., 2017) as used in this study, namely TAM. The theoretical model was assessed by PLS-SEM analysis in a two-stage process related to measurement and structural components. First, the research data were analyzed for validity and reliability by evaluating the average variance extracted (AVE), outer loading, composite reliability (CR), and Cronbach's alpha. Second, testing the Hypotheses using a variance-based Structural Equation Model (SEM) (Hair et al., 2017).

RESULT AND DISCUSSION

Results

Respondents' profile

The demographic profile of respondents was obtained as a result of descriptive statistics. Based on the results of the distribution of questionnaires to respondents, a total of 324 questionnaires could be used for data analysis. Forty percent of respondents (n = 129) were male, while sixty percent were female (n = 195). Then, based on education, as many as twenty-eight percent (n = 90) had a high school education. Thirty-seven percent of respondents (n = 120) with tertiary education, and as many as thirty-five percent (n = 114) with postgraduate/professional education. Based on income, thirty-seven percent of respondents (n = 120) had income < IDR 2,000,000. Thirty-two percent of respondents (n = 105) had income > IDR 2,000,000 - IDR 5,000,000. Then, as many as thirty-one percent (n = 99) incomes> IDR 5,000,000. Based on occupation, thirty-one percent (n = 102) were students. Forty-four percent (n = 141) are civil servants. Ten percent of respondents (n = 33) are private employees, and five percent (n = 15) are self-employed. A small minority of one percent (n = 3) are employees of state companies, and nine percent (n = 30) are outside the group. These results indicate that the respondents are not dominant in any particular group.

Measurement Model

In evaluating the measurement model, convergent and discriminant validity tests were conducted. According to (Chin, 1998), to assess convergent validity, the composite reliability and Cronbach'α for each construct should be higher than 0.7. The average variance extracted (AVE) values should be higher than the recommended threshold of 0.5 (Hair et al., 2017). As explained earlier, six reflective constructs are used in the measurement model (smart tourism technology, perceived usefulness, perceived ease of use, tourist attitudes, travel intentions, and visiting tourism destinations) in addition to the two main criteria for composite reliability (CR) and average variant extracted (AVE).

Table 1. The Reflective Measurement Model

Variable	Measure	Factor loading	Cronbach alpha	CR	AVE
Smart tourism technology	**Smart information system**		0.980	0.982	0.673
	1. Tourist attraction home page	0.827			
	2. Free Wi-Fi	0.842			
	3. Online informationaccess	0.851			
	4. Mobileapplication	0.859			
	5. Quick-responsecode	0.814			
	Intelligent tourism management				
	1. Smart card(band)	0.725			
	2. Electronic entrance guardsystem	0.769			
	3. Tourist-flowmonitoring	0.840			
	4. Crowd handling	0.804			
	5. Smart Education	0.712			
	Smart sightseeing				
	1. Personal-itinerarydesign	0.837			
	2. E-tourism-recommendation system	0.893			
	3. E-tourmap	0.874			
	E-commerce system				
	1. Mobilepayment	0.867			
	2. Online coupons	0.878			
	3. Online booking	0.824			
	Smart Safety				
	1. Intelligent environment monitoring	0.794			
	2. Travel safetyprotection	0.755			
	3. Smart emergency-response system	0.802			
	Intelligent traffic				
	1. Smartvehicle-scheduling	0.803			
	2. Real-time trafficbroadcast	0.822			

Variable	Measure	Factor loading	Cronbach alpha	CR	AVE
	Smart forecast				
	1. Tourist-flowforecast	0.744			
	2. Queuing-timeforecast	0.804			
	3. Weatherforecast	0.803			
	Virtual tourist attraction				
	1. Virtual tourism experience	0.863			
	2. Virtual travel community	0.886			
Perceived usefulness	1. Help in my every trip	0.805	0.788	0.863	0.611
	2. Flexible	0.822			
	3. Saves my time	0.757			
	4. Increase my travel experiences	0.740			
Perceived ease of use	1. It is not difficult to learn	0.852	0.814	0.878	0.644
	2. A clear feature	0.756			
	3. Easy to use	0.746			
	4. Can be learned quickly	0.850			
Tourist attitude	1. The existence of Smart facilities influences my attitude toward visiting this destination	0.881	0.837	0.891	0.672
	2. I can access new facilities like smartphones, websites, etc.	0.841			
	3. Smart facilities are very important to me	0.766			
	4. I expect that every tourist destination should provide smart facilities for visitors	0.785			
Travel intention	1. I intend to visit destinations because of safety and security issues	0.775	0.829	0.897	0.745
	2. For my future travels, I want to go to destinations with more technological facilities	0.906			
	3. I will make an effort to visit destinations with more technology facilities when traveling	0.902			
Visiting tourist destinations	1. I prefer smart destinations rather than traditional ones	0.920	0.858	0.911	0.773
	2. I will select smart destinations for future trips	0.916			
	3. Smart destinations have more to offer compared to traditional destinations; hence I get more experiences	0.796			

Table 1 shows the results of a valid loading factor with a value above 0.7; thus, the indicators can be used in the research model. Discriminant validity is evaluated by comparing an individual construct's AVE with all other constructs, commonly called the Fornell-Larcker criterion. From the results of discriminant validity testing, the square root of each construct's AVE should be higher than the correlation of the construct with other latent variables (Fornell & Larcker, 1981). In addition, cross-loadings of all the items were tested, and the results show that each within-construct item loading is higher on the measured construct than the cross-loadings on the other items, and this indicates the discriminant validity of the measurement model is accepted (Chin, 1998).

Table 2. Discriminant Validity

	1	2	3	4	5	6
1. Visiting tourist destination	0.879					
2. Travel intention	0.675	0.863				
3. Attitude	0.563	0.486	0.820			
4. Perceived usefulness	0.595	0.659	0.762	0.782		
5. Perceived ease of use	0.617	0.580	0.757	0.726	0.830	
6. Smart tourism technology	0.645	0.817	0.463	0.614	0.584	0.820

The discriminant validity analysis using the Fornell-Larcker criterion analysis shows that each construct's square root of Average Variance Explained (AVE) with the variance between constructs and the square root of AVE is greater than the variance between constructs. Consequently, the researcher can state discriminant validity between constructs. Table 4 shows that discriminant validity in the model, the square root of AVE of each construct is greater than the shared variance between the constructs. It can be said that discriminant validity is acceptable.

Structure Model

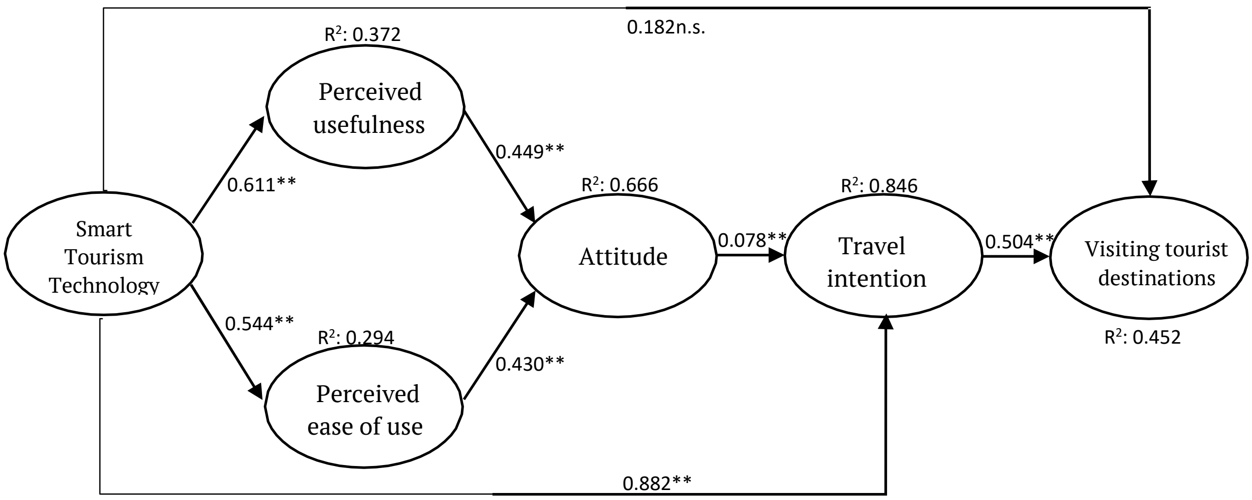
In analyzing the structural model (inner model), two recommended criteria of the significance of the path coefficient and the value of R^2 are applied (Hair et al., 2017). R^2 sizes of 0.75, 0.50, and 0.25 for all endogenous structures, respectively, are considered substantial, moderate, and weak. The results of data analysis show that

R^2 on the attitude variable is 0.666, R^2 on the travel intention variable is 0.846, and R^2 on the visiting tourism destination variable is 0.452. This indicates that each of these variables is influenced by exogenous variables in the substantial and moderate criteria. Next, we examined the direct effect between variables. The structural model test shows the relationship between latent variables with other latent variables. The result of the proposed model's structural estimates and the direct, indirect, and total effect of the variables tested is shown in Table 3. Table 3 exhibits the estimated path coefficient of a direct effect of all variables tested are significant (with β values ranging from 0.078 to 0.882 and significant at $\rho < 0.05$ and $\rho < 0.01$), except the relationship between smart tourism technology on visiting tourism destination (β = 0.182, $\rho > 0.05$). Thus, all hypotheses (H1 to H8) are supported, except for hypothesis H8. The results of the direct effect between variables and the values of R^2 are portrayed in Figure 2.

Table 3. The Hypothesis Testing Results

Path (Hypothesis)	B	T-value	Results
Attitude – travel intention (H1)	0.078	3.563**	Accepted
Perceived usefulness – Attitude (H2)	0.449	9.707**	Accepted
Perceived ease of use – Attitude (H3)	0.430	9.221**	Accepted
travel intention – visiting tourist destination (H4)	0.504	5.019**	Accepted
Smart tourism technology – Perceived usefulness (H5)	0.611	19.509**	Accepted
Smart tourism technology – Perceived ease of use (H6)	0.544	11.883**	Accepted
Smart tourism technology – travel intention (H7)	0.882	64.737**	Accepted
Smart tourism technology – visiting tourist destination (H8)	0.182	1.747	Rejected

To understand the adoption of smart tourism technology, this study also analyzed the indirect and total effects between variables to obtain more complete and comprehensive findings. The test of the indirect effect and total effect variables shows that all of the variable indirect effect and total effects are significant at $p < 0.01$ and $p < 0.05$. Among the total effects, smart tourism technology has the highest effect on total travel intention (β = 0.921). The surprising results showed the effect of smart tourism technology on visiting tourist destinations which did not have a significant direct effect but had an indirect effect (β = 0.464) and a total effect (β = 0.646). These results indicate that smart tourism technology will affect visiting destinations if integrated with TAM.



Notes: **Significant at p < 0.01; ns: not significant

Figure 2. The result of testing the proposed integrated model.

Table 4. Direct and Indirect Effects

Relationships	Direct		Indirect		Total	
	β	T-value	Β	T-value	β	T-value
Attitude – travel intention	0.078	3.563**	–	–	0.078	3.563**
Perceived usefulness – Attitude	0.449	9.707**	–	–	0.449	9.707**
Perceived ease of use – Attitude	0.430	9.221**	–	–	0.430	9.221**
Travel intention – visiting tourist destination	0.504	5.019**	–	–	0.504	5.019**
Smart tourism technology – Perceived usefulness	0.611	19.509**	–	–	0.611	19.509**
Smart tourism technology – Perceived ease of use	0.544	11.883**	–	–	0.544	11.883**

Smart tourism technology – travel intention	0.882	64.737**	0.040	3.393*	0.921	134.798**
Smart tourism technology – visiting tourist destination	0.182	1.747	0.464	4.975**	0.646	22.427**

Notes: *Significance at ρ 0.05; **Significance at ρ 0.01

Discussion

This paper has examined the adoption of smart tourism technology using TAM as the main model in technology acceptance. There are three important findings from this research. First, our findings suggest that TAM can explain the adoption of smart tourism technology. Perceived usefulness and perceived ease of use together affect attitude, which positively affects travel intention. As suggested by TAM (Venkatesh, 2000), the results show that perceived usefulness and perceived ease of use have a positive impact on attitude, and attitude has a positive effect on travel intention (Chen et al., 2017; Ghaderi et al., 2018; Liu et al., 2017; Park et al., 2017). Therefore, Hypotheses 1, 2, and 3 were supported. The results show that perceived usefulness has an effect almost the same as perceived ease of use on attitude. One possible reason is that people are getting used to using smart technology-based products in tourism activities. Thus, they want to try other latest smart-based devices and services to get an easier and more useful traveling process. This will also lead to positive attitudes of tourists if service providers can demonstrate the ability to use smart tourism technology to reduce the effort required for travel and the desired technology proves useful and easy to use. In addition, this study also shows the relationship between travel intention and visiting smart destinations. Thus, hypothesis 4 is accepted. This is in line with Ghaderi et al. (2018) research, which shows a relationship between travel intention and tourist destinations.

This study complements the existing tourism literature regarding important aspects of tourists when evaluating the adoption of smart tourism technology. Smart tourism technology that is easy to use and useful for tourists will affect the attitude of tourists, which will affect travel intention to visit a destination. Thus, this study has successfully proven TAM in adopting smart tourism technology. Compared with previous TAM studies in the context of technology used in tourism (Im & Hancer, 2016; Sahli & Legohérel, 2015), this study reports that the TAM model can explain travel intention in the context of smart tourism technology.

Second, the research results have revealed that smart tourism technology has a significant effect on perceived usefulness and ease of use, which are imperative factors in adopting smart tourism technology. Therefore, Hypotheses 5 and 6 were supported. This finding corroborates with past studies that have shown the relationship between usefulness and ease of use in the field of information systems and technology applications in tourism (Hua et al., 2017; Im & Hancer, 2016; Sahli & Legohérel, 2015). Although these studies support the important role of perceived usefulness and perceived ease of use in technology in tourism, no research proves the effects of smart tourism technology, which has more complete dimensions, on perceived usefulness and perceived ease of use. Several components of smart technology must be present in tourism destinations, such as a smart information system, intelligent tourism management, smart sightseeing, an e-commerce system, smart safety, intelligent traffic, smart forecasting, and virtual tourist attractions (Wang et al., 2016). Tourists in the tech-savvy era had different technological needs from tourists in the pre-Internet / social media era. Thus, better smart tourism technology will make it easier for tourists and provide them with a better experience. The need for smart tourism technology also challenges the tourism industry and develops smart tourism technology that is easy to use and useful for tourists.

Third, this study shows the importance of smart tourism technology in influencing travel intention and visiting tourism destinations. The study results show a significant effect of smart tourism technology on travel intention, supporting hypothesis 7. These results are in line with previous research showing smart tourism technology's effect on intention (Ghaderi et al., 2018; Jeong & Shin, 2019). Among the total effects, the highest influence is on the effect of smart tourism technology on travel intention. This is because destination selection and visit intention are critical aspects of tourist behavior influenced by technological development trends (Ghaderi et al., 2018). In its effect on visiting tourism destinations, surprising results show that smart tourism technology does not have a significant direct effect on visiting tourist destinations, which is different from previous studies (Jeong & Shin, 2019; Yoo et al., 2017), but has an indirect effect on the variables on TAM. This is shown by the total effect of smart tourism technology on visiting tourist destinations. These results prove that integrating smart tourism technology and TAM can affect visiting tourism destinations. Tourists seek suitable facilities and services (Suhartanto, 2017) to enhance their travel experience and influence selecting and visiting tourism destinations (Ghaderi et al., 2018). In addition, smart tourism technology's quality was a starting point for tourists to build a loyal relationship with the destination (Jeong & Shin, 2019). Thus, the findings support the argument that smart tourism technology and TAM play an important role in influencing travel intention, affecting tourist destinations.

CONCLUSIONS

This study has found the influence between the research variables in adopting smart tourism technology. The results show that smart tourism technology significantly affects perceived ease of use and perceived usefulness, which then affects attitude. Travel intention is directly influenced by attitude. Then, travel intention affects visiting tourism destinations. Moreover, integrating smart tourism technology and TAM models is the most suitable model for explaining technology's role in influencing visiting destinations. This integration shows the important role of smart tourism technology's usefulness and ease of use in influencing visiting destinations.

Theoretically, this study has proposed and empirically tested a research model that integrates smart tourism technology and TAM using partial least squares - structural equation modeling. These results indicate that TAM can help predict and understand the adoption of smart tourism technology. Although there is much research related to TAM in the tourism industry, this theory has been successfully applied in a broad spectrum of tourism research (Hua et al., 2017; Nunkoo et al., 2016; Tussyadiah et al., 2017; Xia et al., 2018). However, this study is the first to integrate smart tourism technology and TAM in a single comprehensive model for predicting travel intention and visiting tourist destinations. Current research shows that this model can be an analytical tool for adopting smart tourism technology.

In practice, in the analysis of the adoption of smart tourism technology as a predictor of visiting tourist destinations, various stakeholders such as the Government and tourism service providers need to mobilize resources for technology development by prioritizing ease of use and usefulness of smart tourism technology. This is an alternative strategy for destination excellence in the competitive tourism industry. Collaboration between tourists, tourism service providers, and the government must provide continuous emotional and psychological support to build technology in tourism in Indonesia. In addition, joint collaboration is needed to manage tourism technology in Indonesia by continuously updating existing technological facilities. Technology standards and safety standards for smart tourism technology must also be emphasized to ensure tourists get a safe, comfortable, and guaranteed travel environment.

LIMITATIONS AND FUTURE RESEARCH

Although this research has succeeded in expanding the understanding of the adoption of smart tourism technology by integrating TAM, like most studies, several limitations must be mentioned. First, the data obtained in this study was obtained from the perspective of tourists visiting West Java Province, Indonesia. Thus, the results of this research cannot be generalized to other tourists around the world. To broaden generality, future research can measure the association between the variables in other regions and countries. Second, this study is concentrated on the influence of smart tourism technology, perceived usefulness, perceived ease of use, and attitude as the drivers of travel intention to visit a tourist destination. However, there may be other variables that could potentially affect the adoption of smart tourism technology. In addition, other models can explain the adoption of smart tourism technology, such as the UTAUT model. Future research could integrate this other model into the existing model adoption. Third, each tourist destination has different attraction characteristics and attraction themes, which may also vary the characteristics of the tourists. This will affect the behavior of tourists at each destination. Future research may wish to focus on the characteristics and themes of attractions as the focus of their research, to analyze tourist behavior more precisely.

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