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The effect of the perceived risk on the adoption of the sharing economy in the tourism industry: The case of Airbnb

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ABSTRACT

Smart tourism and the sharing economy within it are transforming human lives and are considered a huge innovation in the industry. This change inevitably creates huge resistance, which did not obtain much attention. Thus, this study focuses on sharing economy's risk aspects, which have become a social issue. It investigates how risks affect the development and diffusion of the sharing economy, especially in Airbnb. This study adopts extended model of goal-directed behavior and depicts the decision-making process of potential Airbnb users to analyze risk effect. Results of structural equation modeling applied to 300 potential customers indicate that privacy and financial risks negatively affect the intention to use the sharing economy. However, physical and performance risks are positively related with behavioral intention or desire. This risk paradox can be explained by the disruptive innovation of the sharing economy and the characteristics of risk engagement in tourism. Implications for research and practice are discussed along with the findings of the study.

1. Introduction

Information infrastructure and social and human capital in the smart tourism connect residents, business entities, and visitors, creating a complex business ecosystem (Gretzel, Sigala, Xiang, & Koo, 2015). Sharing economy is one of the most representative business ecosystems. Sharing economy and collaborative consumption are new concepts born from Web 2.0 and mobile technology, which constitute the core of smart tourism cities (Frenken & Schor, 2017). Sharing economy coordinates the acquisition and distribution of goods for a fee or other forms of compensations; this scheme is called "collaborative consumption" in the academia (Belk, 2014).

In contrast to traditional defenders, the peer-to-peer service system in sharing economy provides cost leadership and also suggests a new way of life among local communities via interactive communication (Botsman & Rogers, 2010; Guttentag, 2015; Tussyadiah, 2015). The financial crisis and the emerging trend of the fully independent tourist accelerated the growth of sharing economy, especially in the travel and tourism marketplace (Sacks, 2011; Zervas, Proserpio, & Byers, 2017). Interestingly, this growth also affected travel patterns, such as increasing frequency, length of stay, and local spending (Airbnb, 2015; Tussyadiah & Pesonen, 2016).

The incredible valuations and the rapid growth of the sharing economy have filled the industry and academia with optimism regarding its bright future. However, various threats and risks still linger. For instance, the safety concern related to the sharing economy becomes serious social issues (Ert, Fleischer, & Magen, 2016; Guttentag, 2015). Although the reputation-related technologies in sharing economy provide the basis of trust among strangers, these technologies could not prevent crimes and accidents, from

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robbery and sexual assault to homicide (Arrington, 2011; Bever, 2018; Lieber, 2015; Malhotra & Van Alstyne, 2014). However, these crimes are also hard to prevent in the traditional tourism business. Hyper reaction from the media has exaggerated the fears regarding the safety of sharing economy and general uncertainties associated with strangers (Guttentag, 2015).

Although the sharing economy is a new type of business, containments from the traditional industry and user concerns seem to be a bit excessive. This, as the core of the sharing economy is a new technological innovation that naturally causes resistance among adopters (Ert et al., 2016; Ram & Sheth, 1989). In this regard, the whole decision-making-process of tourists regarding the adoption of sharing economy should be analyzed to fully understand the current phenomenon. Fortunately, various scholars studied the decision-making process of the customers of sharing economy due to the fast-growing interest on sharing economy, and they found that the key is sustainability and authentic experience from the local community (Guttentag, 2015; Liang, Choi, & Joppe, 2018; Tussyadiah, 2016). However, the role of the perceived risks during the process is not yet fully considered (Lutz, Hoffmann, Bucher, & Fieseler, 2018).

In this context, the current study focuses on the following. First, it uses the model of goal-directed behavior (MGB), an extension of theory of planned behavior (TPB), to investigate the key risk factors in the adoption of sharing economy, especially for Airbnb. Second, this study focuses on the perceived risks and explores what and how risks affect adoption, which has been ignored by previous studies. We will also explore the balance between the traditional accommodation business and the sharing economy when constructing a smart tourism ecosystem.

2. Theoretical background and hypotheses

2.1. Smart tourism and the model of goal-directed behavior

The smart tourism tradition studied the convergence of information technology innovations, business models, and touristic experiences, and it provided the basic understanding of sharing economy in the perspective of smart tourism cities. Studies in smart tourism can be categorized into the following major streams (Gretzel et al., 2015; Wang, Xiang, & Fesenmaier, 2014): (1) the design aspects of the ecosystem of a smart tourism city (Brown, Kappes, & Marks, 2013; Koo, Shin, Gretzel, Hunter, & Chung, 2016; Zhu, Zhang, & Li, 2014), (2) adoption of new innovations in travel (Eriksson & Strandvik, 2008; Kim, Ahn, & Chung, 2013; Oh, Lehto, & Park, 2009; Peres, Correia, & Moital, 2011), and (3) the impact of innovations on the tourist experience (Buhalis & Amaranggana, 2015; Wang, Park, & Fesenmaier, 2012).

Various theories in social science were used to understand customer behaviors under the innovations of smart tourism. Among these theories, the theory of reasoned action (TRA) and TPB have been frequently used to depict the decision-making process of tourists in smart tourism (Chung, Lee, Lee, & Koo, 2015; French, Luo, & Bose, 2017; Koo & Chung, 2014). Based on TRA, which assumes that the decision-making of customers is made by attitude and subjective norm, TPB believes that behavioral control is also important to understand the mind of customers (Ajzen, 1991). TRA and TPB have several limitations, despite their wide-scale adoption in tourism studies because of their parsimony and high predictability. These theories only consider the rational part of the decision-making process, disregarding the emotional and hedonic characteristics of customer behaviors (Hong & Tam, 2006; Turel, Serenko, & Bontis, 2010). In addition, these theories do not include goal and motivation, which are crucial in human behaviors, in the decision-making process model (Bagozzi, 1992). Thus, Perugini and Bagozzi (2001) suggested MGB. The main difference between TPB and MGB is that MGB uses desire, rather than attitude, to explain the behavioral intention. An attitude is a tendency of preference to a particular entity, whereas a desire shows if motivations exist to do or achieve something in mind (Perugini & Bagozzi, 2004). In this regard, the attitude is a result of the rational evaluation, but the desire is a comprehensive result from the rational, emotional, and social aspects (Bagozzi & Dholakia, 2006). Thus, MGB reconstructs TPB and assumes that attitude and subjective norm indirectly affect the behavioral intention through desire (Perugini & Bagozzi, 2001). Based on prior literature studies, the following hypotheses have been developed.

H1. Attitude positively affects the desire to adopt Airbnb.

H2. Subjective norm positively affects the desire to adopt Airbnb.

The emotional and the functional values are equally important in the decision-making of consumers (Turel et al., 2010). Experiential and hedonic goods as well as functional and physical products also provide emotional value. Phenomena such as love of a car and hedonic buyers of new technologies imply that emotion is one of the key factors in smart tourism (Hong & Tam, 2006; Yoo, Kwon, Na, & Chang, 2017).

Individuals experience prior emotions through the imagination of certain situations associated with planned behavior. The anticipated emotions include positive and negative valence. In MGB, positive anticipated emotion means emotions to be felt if the individual *succeeds* in achieving a goal-directed behavior, whereas negative anticipated emotion means emotions to be felt if the individual *fails* to achieve a goal-directed behavior. A positive correlation exists between these two constructs yet they are differentiated. (Perugini & Bagozzi, 2001). Negative as well as positive anticipated emotions might have positive effects on desire because it is related to the wish to prevent situations of failing to achieve the goal. Customers feel prior emotions about future actions, especially when faced with uncertainty. Thus, the balance between positive anticipated emotion about goal attainment and the negative anticipated emotion about goal failure effectively predict the desire to a specific action but are intentionally not included in TPB (Bagozzi, Baumgartner, & Pieters, 1998; Perugini & Bagozzi, 2001). The following hypotheses have been developed based on prior literature:

H3. Positive anticipated emotion positively affects the desire to adopt Airbnb.

H4. Negative anticipated emotion positively affects the desire to adopt Airbnb.

Generally, the magnitude of one's intention to perform a specific action is strongly affected by the resources and opportunities for the action (Ajzen, 1991). Thus, the perceived behavioral control (PBC) works as a key variable to explain the reason for the action, and it becomes the core of TPB. MGB inherited the importance of PBC from TPB, and it assumes that PBC reinforces the desire and the intention of a specific behavior (Perugini & Bagozzi, 2001). The empirical studies of MGB also support these relationships (Song, Lee, Kang, & Boo, 2012; Song, Lee, Norman, & Han, 2012; Taylor, Ishida, & Wallace, 2009). The following hypotheses have been developed based on prior literature:

H5. PBC positively affects the desire to adopt Airbnb.

H6. PBC positively affects the intention to adopt Airbnb.

MGB uses the desire as a sole proxy variable for the intention to effectively explain the motivation and the goal-directed behavior of customers. Bagozzi (1992) showed that intention can be explained without evaluating reaction, but the desire is essential for the development of an intention. Fishbein and Stasson (1990) also proved that desire has more explanatory power than the attitude for the intention of a specific behavior.

Peruguni and Bagozzi (2004) explain the difference between desire and intention in three dimensions. First, intention needs a certain level of self-confidence for specific actions, but desire does not necessarily need it. Second, intention has stronger connection to goals or outcomes in comparison with desire. Intention needs a physical form of plans or commitment for achieving the intended behavior. On the contrary, desire is more abstract than intention. Finally, intention is relatively now-oriented, but desire usually does not have time limitation. These differences clearly show that desire is ahead of intention in the psychological processing phases. Thus, we propose the following hypothesis:

H7. Desire positively affects the intention to adopt Airbnb.

2.2. Perceived risk

Previous Airbnb research has mostly focused on Airbnb users to investigate why they use the service or from which factors they were satisfied (e.g., Guttentag, Smith, Potwarka, & Havitz, 2017; So, Oh, & Min, 2018; Wang & Jeong, 2018), and potential users relatively lack understanding. Given that the benefits of Airbnb is difficult to guarantee before adoption, potential users who have never used the service face a higher level of uncertainty than current users. In the context of consumer behavior, the risk is conceptualized as a subjective feeling of uncertainty if the results of purchase will be favorable or a subjective expectation of a potential loss (Dholakia, 2001; Quintal, Lee, & Soutar, 2010; Sweeney, Soutar, & Johnson, 1999). Given that various types of risk might cause adoption resistance among potential users, this constraint is crucial in understanding the decision-making process of potential users (Quintal et al., 2010). However, MGB does not properly consider the psychological barriers that potential adopters may face. A few studies on tourism have attempted to reflect the risk impact on desire and intention by expanding MGB. For instance, Lee, Song, Bendle, Kim, and Han (2012) suggested an extended model that considers perceived risk from an influenza virus as an obstacle that could discourage tourists from visiting foreign countries. Although the researchers did not directly measure perceived risks, certain studies also included past experience as a determinant of desire and intention from the consideration that it diminishes the perceived risk associated with decisions regarding casino visits (Song, Lee, Kang et al., 2012; Song, Lee, Norman et al., 2012) or wine tour participation (Lee, Bruwer, & Song, 2017). Moreover, several studies based on TPB have considered the role of risk in the decision-making of tourists (e.g., Lam & Hsu, 2006; Quintal et al., 2010; Wang & Ritchie, 2012) These studies have consistently suggested that perceived risk influences the desire of consumers and thus behavioral intentions. Airbnb is growing at a rapid pace, but its unique operating structure has also raised concerns. Given that Airbnb accommodation is a private space provided by individual hosts, it is difficult to maintain consistent quality levels in accordance with the manual. Therefore, the potential users of Airbnb will have a high level of uncertainty and face various risk factors. The present research will suggest an extended model of goal-directed behavior (EMGB) by integrating perceived risk theory into MGB. In contrast to previous studies that measured perceived risks in a single construct (e.g., Schmiege, Bryan, & Klein, 2009), the present study will draw risk factors which are relevant to Airbnb through a literature review of perceived risk theory and include those specific risk factors in MGB.

Starting from Bauer (1960), consumer perceptions of risk have been widely studied and shown to influence various aspects of consumer decisions and behaviors (Bauer, 1960; Cunningham, Gerlach, Harper, & Young, 2005). The perceived risk originally refers to the nature and amount of the risk perceived by a consumer in contemplating a particular decision (Cox & Rich, 1964), but it eventually expanded to cover the whole decision-making process (Taylor, 1974), and even the adoption of innovations of a consumer (Featherman & Pavlou, 2003).

In contrast to risk in business or countries, the perceptions of risk in consumers' activities are situation specific and should be evaluated using measures in the context of interest. Thus, perceived risks are subjectively measured (Dowling, 1986). Subjective measures tend to be intensified in the evaluation of risks associated with travel. Given the intangible and experiential nature of tourism, the expected outcome of travel is essentially uncertain. High-involvement aspects of tourism services also increase the importance of perceived risk in the tourism industry (Sirakaya & Woodside, 2005). Moreover, the perceived risk of travelers is likely to be high because most travel experience relies on intangible, heterogeneous, and hard-to-standardize services (Roehl & Fesenmaier, 1992).

Perceived risk works as an important factor of tourists' decision-making process (Floyd, Gibson, Pennington-Gray, & Thapa, 2004; Maser & Weiermair, 1998; Quintal et al., 2010). High-risk perception leads to the avoidance of certain tourism destination, buying channels, and transportation (Cunningham et al., 2005; Quintal et al., 2010; Sönmez & Graefe, 1998). High-risk perception also negatively affects travel intention (Floyd et al., 2004) and compels tourist to invest more time searching related information for risk aversion (Maser & Weiermair, 1998).

On the contrary, some tourism studies recalled that the essence of tourism lies in the risk-pursuit activity. Thus, the key objective of risk management of tourists is not to avoid risk but to control the risk level properly (Cater, 2006). Studies on leisure activities, adventure tourism, international tourism, and backpacking also suggested that the perceived risk is a positive cause for selection in the decision-making process of tourists (Cater, 2006; Dickson & Dolnicar, 2004; Elsrud, 2001; Lepp & Gibson, 2003).

The perceived risk of technology adoption negatively affects customers' behavior. When consumers consider the adoption of a new technology, they fall into a dilemma between its desirable and undesirable consequences, and they have to face a risk decision. Perceived risk in the technology adoption perspective is a function of its unexpected results, and an outcome from the expectation (Featherman & Pavlou, 2003; Hirunyawipada & Paswan, 2006). High-risk perception directly influences the intention to adopt and leads to the non-adoption of a new technology (Featherman & Pavlou, 2003; Liébana-Cabanillas, Sánchez-Fernández, & Muñoz-Leiva, 2014; Oliveira, Thomas, Baptista, & Campos, 2016; Slade, Dwivedi, Piercy, & Williams, 2015). However, the negative effect of the perceived risks on the decisions of customers is not as obvious as predicted (DelVecchio & Smith, 2005; Mitchell & Harris, 2005). These contradictory findings could be a result of behavioral changes under high-risk perception, such as seeking further information and mitigating or managing risk levels (Hirunyawipada & Paswan, 2006).

Among the various risks of sharing economy, physical risk, which directly related to the safety, obtains much attention through the media. To ensure safety of transaction among strangers, sharing economy has developed various trust proof mechanisms using platform technology, but service failure is inevitable (Ert et al., 2016). Various cases of service failure, such as robbery, sexual assault, and violence, were found and reported by the mass media (Arrington, 2011; Bever, 2018; Guttentag, 2015; Malhotra & Van Alstyne, 2014). The reported service failure cases showed that the safety failure of sharing economy causes physical and financial damage to the unfortunate tourists (Lieber, 2015). The following hypotheses have been developed based on prior literature.

H8. Physical risk negatively affects the desire to adopt Airbnb.

H9. Physical risk negatively affects the intention to adopt Airbnb.

H10. Financial risk negatively affects the desire to adopt Airbnb.

H11. Financial risk negatively affects the intention to adopt Airbnb.

The sharing of personal information through the platform also creates privacy concerns. Online service naturally requires various personal information during the transaction, and user information is inevitably exposed to accidental and intentional harms (Culnan & Armstrong, 1999; Malhotra, Kim, & Agarwal, 2004). Thus, reducing privacy risk during online transaction becomes one of the core success factors in the online service industry (Hoffman, Novak, & Peralta, 1999). Privacy risk becomes crucial in the sharing economy. The nature of sharing economy requires the transaction of personal information in the virtual and physical world, and this requirement increases the potential threat level of privacy (Belk, 2014; Lutz et al., 2018).

Another concern of sharing economy is the performance risk. In comparison with the industrialized and standardized service in the traditional accommodation business, Airbnb listings, which are managed by amateurs, generally show lower performance in the basic functions of accommodation service (Guttentag, 2015; Zervas et al., 2017). Potential Airbnb customers are seriously concerned with this risk when considering accommodation (Guttentag & Smith, 2017).

The following hypotheses have been developed based on prior literature.

H12. Privacy risk negatively affects the desire to adopt Airbnb.

H13. Privacy risk negatively affects the intention to adopt Airbnb.

H14. Performance risk negatively affects the desire to adopt Airbnb.

H15. Performance risk negatively affects the intention to adopt Airbnb.

The theoretical model in Fig. 1 is proposed based on the aforementioned hypotheses.

3. Research methods

3.1. Sample and data collection

Korean tourists who have not experienced or used Airbnb participated in the survey, which was conducted from March 19 to 22, 2018. Questionnaires were distributed to online survey panels provided by Korean Research, a marketing research firm in Korea. Respondents were recruited using quota sampling, which consider gender and age groups. A total of 300 usable questionnaires were collected for data analysis.

Table 1 shows that gender was evenly distributed among 150 (50%) males and 150 (50%) females. The average age of the respondents was 39.85, and the age group was evenly distributed between their 20 s and 50 s. Most respondents had a university degree (214, 71.3%), followed by a high school diploma (55, 18.3%) and graduate school (31, 10.3%). A total of 130 respondents (43%) had a monthly household income of 2.5 m–5 m Korean won (about 25k–50k USD), which is a typical middle class income in Korea. Lastly, 236 respondents (78.7%) stated they had experience traveling abroad (See Table 1).

Theory of Planned Behaviour

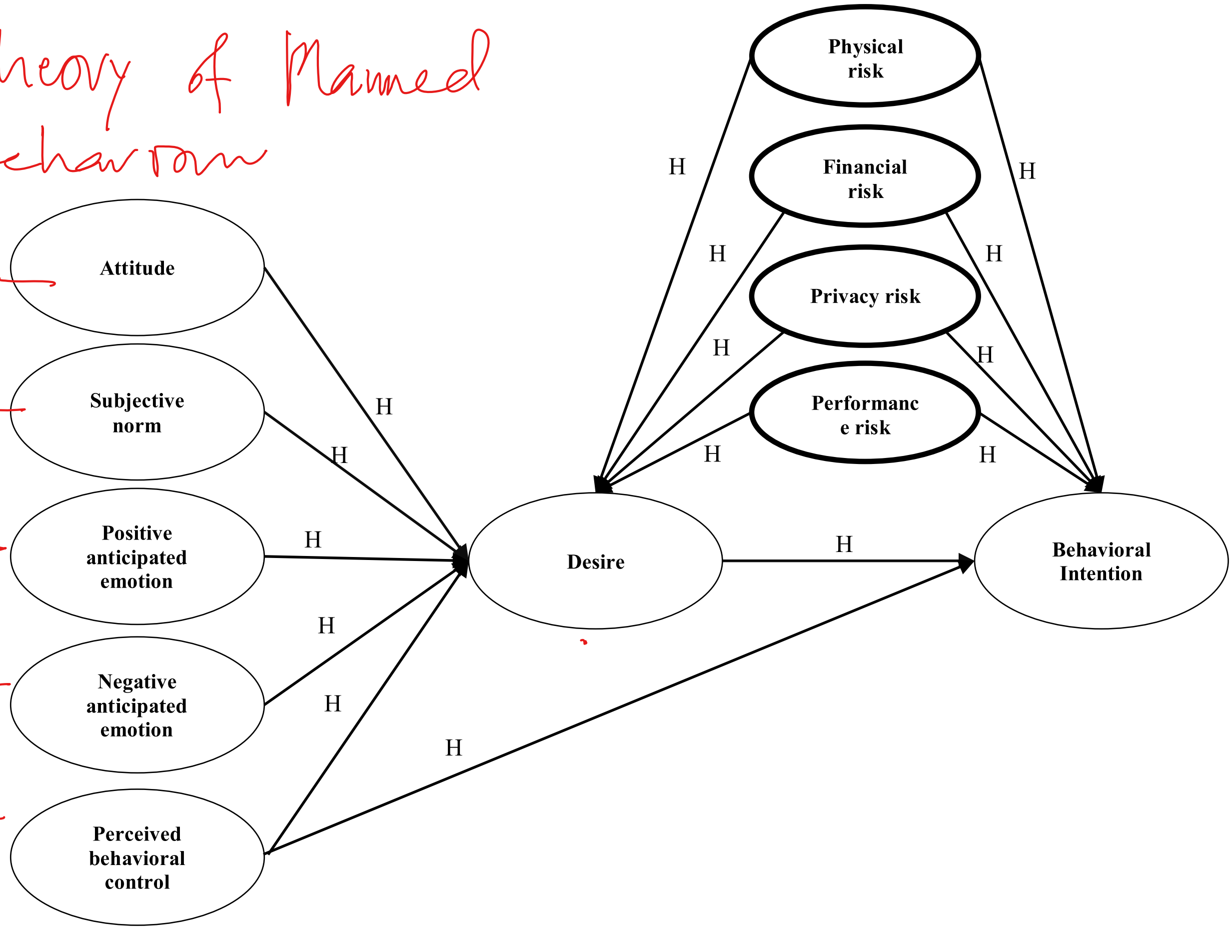

Fig. 1. A proposed research model.

Table 1
Respondents' demographical characteristics.

Characteristics		Frequency	%
Gender	Male	150	50%
	Female	150	50%
Age	20 ~ 29	74	24.6%
	30 ~ 39	76	25.3%
	40 ~ 49	76	25.3%
	50 ~ 59	74	24.6%
Education	High school	55	18.3%
	University	214	71.3%
	Graduate school	31	10.3%
Income (KRW 1000)	Less than 9999	33	11%
	10,000–24,999	79	26.3%
	25,000–49,999	130	43.3%
	50,000–74,999	35	11.7%
	75,000–99,999	15	5%
	More than 100,000	8	2.7%
Overseas travel experience	Yes	236	78.7%%
	No	64	21.3%%
Total		300	100

3.2. Measurement and analysis method

The research model includes 11 variables—seven from MGB (attitude, subjective norm, positive anticipated emotion, negative anticipated emotion, perceived behavioral control, desire, and behavioral intention) and four from perceived risk theory (physical, financial, privacy, and performance risks). Items were adapted from extant literature and modified to fit the context of sharing economy and accommodation service. Items of MGB were adapted from Lee et al. (2012), Perugini and Bagozzi (2001), Song, Lee, Kang et al. (2012) and Song, Lee, Norman et al. (2012). PBC was measured with three items, and other variables were measured with four items. Items of the risk variables were adapted from Dholakia (2001), Featherman and Pavlou (2003), andRoehl and Fesenmeir (1992). Physical and performance risks were measured with four items each, whereas financial and privacy risks were measured with three items each. All items were assessed on a five-point Likert scale from strongly disagree (1) to strongly agree (5).

The collected data were analyzed with structural equation modeling (SEM) using AMOS 22.0. The structural relationships were examined, and the hypotheses were tested after conducting confirmatory factor analysis (CFA) on the measurement model.

4. Analysis and results

4.1. Measurement model

CFA was conducted to investigate the reliability and validity of the constructs. The measurement model provides a good fit to the data (χ^2 = 1387.089, df = 724, p < 0.001, χ^2/df = 1.916, CFI = 0.929, GFI = 0.810, IFI = 0.930, NNFI = 0.919, RMSEA = 0.055). Most fit indices satisfy the criteria of above 0.9, as suggested by Bagozzi and Yi (1988). Although GFI does not exceed 0.9, the value meets the 0.8 acceptability requirement of Baumgartner and Homburg (1996).

For testing reliability, we applied the Cronbach alpha indicator with 0.7 as the reference value (Cortina, 1993). All alpha values exceed 0.7, indicating a good reliability. We then tested convergent validity, which refers to the degree of consistency of the observations that measure the potential variables using three criteria suggested by Fornell and Larker (1981), namely, factor loadings, composite reliabilities (CR), and average variance extracted (AVE). All item factor loadings were significant and exceeded 0.60. The CRs of all factors also exceeded 0.80, the required minimum by Hair, Black, Babin, and Anderson (2010). In addition, all AVEs are over 0.5, suggesting a good convergent validity of all constructs (See Table 2).

Discriminant validity was tested using the recommendation of Fornell and Larcker (1981) that the square root of AVE for each construct should exceed the correlations of all other constructs. Table 3 shows that the square root of AVE is greater than its correlation coefficients with other factors, suggesting a good discriminant validity of the current model.

4.2. Hypothesis testing

Fit index evaluation and model comparison were conducted before testing the hypothesis. The proposed structural model fits data well (χ^2 = 1481.066, df = 748, p < 0.001, χ^2/df = 1.980, CFI = 0.921, GFI = 0.797, IFI = 0.922, NNFI = 0.914, RMSEA = 0.057). Although GFI (0.797) does not meet the criteria (>0.9), other fit indices consistently indicate that this model is applicable for the hypothesis testing. In terms of model comparison, the EMGB, which is the proposed model in this research, was compared with the original MGB of Perugini and Bagozzi (2001). Table 4 summarized the comparison results. The Chi-square difference test (Byrne, 2006) indicated that a significant difference exists between the two models (χ^2 (441) = 823.556 > $\chi^2_{0.001}$ = 538.501). The squared multiple correlation for desire improved from 0.750 to 0.761, and behavioral intention from 0.778 to 0.811 by including four types of perceived risk. Overall, the results show that the extended model with the perceived risk performs better than the original MGB when explaining the decision-making process of potential Airbnb users.

The results of estimated parameter and hypothesis testing are listed in Table 5. As expected, attitude positively affected (β = 0.192, p = 0.040) the desire to adopt Airbnb, thereby supporting H1. Although marginally significant (p < 0.10), the coefficient of the relationship between subjective norm and desire was also positive (β = 0.139, p = 0.064), thereby supporting H2. For the anticipated emotions, positive (β = 0.452, p < 0.001) and negative (β = 0.172, p < 0.001) anticipated emotions showed the positive and significant effects on desire. Thus, H3 and H4 were also supported. H5 and H6 posited that PBC positively affects desire and behavioral intention, respectively. The results showed that the positive effect of PBC on desire was significant (β = 0.087, p = 0.043). However, the effect of PBC on intention was not significant (β = −0.045, p = 0.251, n.s.). Thus, an individual's confidence in being able to use Airbnb does not directly affect the behavioral intention but indirectly through the desire to use the service. As expected, desire and behavioral intention (β = 0.888, p < 0.001) were also positive and significant, thereby supporting H7. Overall, attitude, subjective norm, positive and negative anticipated emotion, and PBC played an essential role in the formation of the consumers' desire, which affects the intention to adopt Airbnb.

From H8 to H15, the model tried to examine the influences of various risks on the desire and the intention to adopt Airbnb. In contrast to expectation, only financial (β = −0.134, p = 0.013) and privacy risks (β = −0.128, p = 0.019) negatively and significantly affected behavioral intention. Thus, only H11 and H13 were supported. The results suggest that, among various risks, financial and privacy risks are two major constraints on Airbnb adoption.

Furthermore, we also found interesting results regarding the relationships between perceived risk and adoption of Airbnb. Physical risk positively affected behavioral intention (β = 0.188, p < 0.001), and performance risk positively affected desire (β = 0.155, p = 0.001). This finding is contradictory to the traditional risk theory and consumer behavior literature, but it is consistent with the phenomenon called "privacy paradox" or "risk perception paradox" (Acquisti & Grossklags, 2005; Lutz et al., 2018; Wachinger, Renn, Begg, & Kuhlicke, 2013). Numerous risk studies found that a discrepancy exists between the perceived risk and the actual behavior of customers, and this discrepancy is frequently found in the online business environment (Gerber, Gerber, & Volkamer, 2018). Although many theories were applied to explain the risk paradox, no united theory exists until now. Extensive reviews show that risk paradox happens when a bias exist in interpreting the risk environment (Barth & de Jong, 2017). In our case,

Table 2
Reliability and confirmatory factor analysis.

Variable	Items	Factor loadings	C.R.	AVE	Cronbach's α
Attitude (ATT)	I think that using Airbnb is a desirable behavior.	0.797	0.943	0.807	0.9
	I think that using Airbnb is useful.	0.804			
	I think that using Airbnb is a wise behavior.	0.866			
	I think that using Airbnb is valuable.	0.861			
Subjective norm (SN)	Most people who are important to me will highly recommend using Airbnb.	0.864	0.943	0.805	0.921
	Most people who are important to me will actively consider using Airbnb.	0.871			
	Most people who are important to me will use Airbnb.	0.858			
	Most people who are important to me will agree with that I use Airbnb.	0.859			
Positive anticipated emotion (PAE)	If I use Airbnb, I will be satisfied.	0.842	0.913	0.726	0.874
	If I use Airbnb, I will be happy.	0.815			
	If I use Airbnb, it will be memorable for a long time.	0.736			
	It will be fun to use Airbnb.	0.782			
Negative anticipated emotion (NAE)	If I can't use Airbnb, I will be worried.	0.697	0.929	0.768	0.911
	If I can't use Airbnb, I will be disappointed.	0.863			
	If I can't use Airbnb, I will be sorry.	0.875			
	If I can't use Airbnb, I will be sad.	0.943			
Perceived behavioral control (PBC)	I am confident that it's up to my will to use Airbnb.	0.771	0.817	0.608	0.734
	The decision to use Airbnb lies entirely with me.	0.846			
	There is no impediment to my use of Airbnb.	0.518			
Physical risk (PHR)	I am afraid the Airbnb host is going to commit a crime to me.	0.889	0.921	0.745	0.906
	Using Airbnb increases the risk of being harmed by criminals.	0.865			
	Using Airbnb can increase my chances of being a target of sexual harassment or sexual assault.	0.865			
	Using Airbnb is likely to increase the risk of accidents while traveling.	0.748			
Financial risk (FNR)	Using Airbnb will be more expensive than using conventional hotels.	0.595	0.823	0.61	0.752
	It is likely that the costs will actually be higher than those proposed by Airbnb.	0.777			
	I think I will get a lower service compared to the money I paid to Airbnb.	0.757			
Privacy risk (PVR)	Using Airbnb may make privacy of payment information uncontrolled.	0.698	0.872	0.696	0.827
	If I use Airbnb, there is a possibility that my personal information may be leaked without my knowledge.	0.886			
	If I use Airbnb, I think hackers or criminals will be able to access my account.	0.78			
Performance risk (PFR)	I am worried that Airbnb would not provide me with the level of benefits that I expected it to.	0.755	0.928	0.763	0.895
	I am worried that the information on the Airbnb Website might be different from the actual accommodation.	0.829			
	I am afraid that the sanitation at the accommodation is below expectations when using Airbnb.	0.84			
	I am concerned that my request or complaint at the accommodation may not be handled promptly when using Airbnb.	0.872			
Desire (DE)	If I travel, I want to choose to stay through Airbnb.	0.83	0.928	0.763	0.907
	I would like to use Airbnb in the near future.	0.865			
	My desire for using Airbnb in the near future is Very weak (1)-Very strong (5)	0.832			
	If I can use Airbnb in the near future, I won't miss that opportunity.	0.851			
Behavioral intention (BI)	I think I will be using Airbnb in the future.	0.889	0.941	0.801	0.922
	I plan to use Airbnb in the future.	0.897			
	I am thinking of using Airbnb in the future.	0.901			
	I intend to try and use Airbnb within a year.	0.779			

Table 3
Discriminant validity eest.

	1	2	3	4	5	6	7	8	9	10	11
1. ATT	**0.898**										
2. SN	0.807	**0.897**									
3. PAE	0.837	0.773	**0.852**								
4. NAE	0.446	0.488	0.485	**0.876**							
5. PBC	0.229	0.184	0.256	−0.097	**0.780**						
6. PHR	−0.305	−0.363	−0.316	−0.243	−0.048	**0.863**					
7. FNR	−0.206	−0.188	−0.271	−0.035	−0.305	0.529	**0.781**				
8. PVR	−0.210	−0.195	−0.233	−0.139	−0.097	0.609	0.531	**0.834**			
9. PFR	−0.085	−0.214	−0.130	−0.228	0.087	0.517	0.609	0.529	**0.873**		
10. DE	0.797	0.747	0.827	0.539	0.277	−0.066	−0.257	−0.230	−0.345	**0.874**	
11. BI	0.678	0.629	0.763	0.412	0.232	−0.034	−0.290	−0.279	−0.245	0.866	**0.895**

*Diagonal elements (bold) show the square root of the average variance extracted (AVE).

Table 4
Model Comparison.

Fit Index	χ^2	df	p	χ^2/df	RMSEA	CFI	NNFI	R^2_{Desire}	R^2_{BI}
MGB	657.510	510	0.000	2.142	0.062	0.947	0.939	0.750	0.778
EMGB	1481.066	748	0.000	1.980	0.057	0.921	0.914	0.761	0.811

Table 5
Hypothesis test results.

	Path			Unstandardized coefficient	Standardized coefficient	S.E.	p-value	H Test
H1	Attitude	→	Desire	0.186	0.192	0.090	0.040*	Supported
H2	Subjective norm	→	Desire	0.123	0.139	0.067	0.064+	Supported
H3	Positive anticipated emotion	→	Desire	0.438	0.452	0.092	***	Supported
H4	Negative anticipated emotion	→	Desire	0.129	0.172	0.034	***	Supported
H5	Perceived behavioral control	→	Desire	0.103	0.087	0.051	0.043*	Supported
H6	Perceived behavioral control	→	Behavioral intention	−0.061	−0.045	0.053	0.251	Rejected
H7	Desire	→	Behavioral intention	1.007	0.888	0.063	***	Supported
H8	Physical risk	→	Desire	−0.072	−0.089	0.045	0.107	Rejected
H9	Physical risk	→	Behavioral intention	0.173	0.188	0.050	***	Rejected
H10	Financial risk	→	Desire	−0.005	−0.005	0.056	0.931	Rejected
H11	Financial risk	→	Behavioral intention	−0.158	−0.134	0.063	0.013*	Supported
H12	Privacy risk	→	Desire	−0.077	−0.083	0.052	0.138	Rejected
H13	Privacy risk	→	Behavioral intention	−0.134	−0.128	0.057	0.019*	Supported
H14	Performance risk	→	Desire	0.137	0.155	0.042	0.001*	Rejected
H15	Performance risk	→	Behavioral intention	0.046	0.046	0.046	0.320	Rejected

* $p < 0.05$, *** $p < 0.001$.

we believe that the disruptive innovation and voluntary nature of risk engagement in tourism cause strong biases to the potential adopters when interpreting the risk.

A disruptive technology is a technology that changes the bases of competition by changing the performance metrics along which firms compete (Bower & Christensen, 1995). Thus, new products in disruptive technology initially have low performance on dimensions relevant to the mainstream market but have high performance on dimensions valued by remote or emerging markets. As new products market evolves, the disruptive technology meets the performance dimension of the mainstream and then engulfs the mainstream market (Danneels, 2004). Airbnb and other accommodation services in sharing economy have lacked many areas for typical tourists like service quality, staff friendliness, brand reputation, and security, which are all important in traditional accommodation industry (Guttentag, 2015). However, sharing economy provides different values, such as exotic experience and local community along with cost leadership (Tussyadiah, 2015).

Scholars in the fields of backpacking, adventure tourism, and international tourism also found that perception of risk increases with the degree of novelty associated with a particular destination (Elsrud, 2001) and concluded that the voluntary nature of risk engagement in leisure and tourism activity is an important factor (Cater, 2006; Dickson & Dolnicar, 2004; Lepp & Gibson, 2003). In contrast with the risk level of ordinary life, tourism activity itself is a risk-seeking behavior, and the decision-making process in the tourism deals with an uncertain outcome and risky situation. Thus, controlling the proper risk level is one of the main objectives in the information processing of tourism (Dickson & Dolnicar, 2004; Maser & Weiermair, 1998). In this regard, physical and performance risks can be considered well controlled by mobile platform provided by Airbnb. Although the potential adopters perceived high risk level, it could be regarded as a calculated risk, which can be adjusted by various trust mechanisms in sharing economy. The high risk level, in turn, can enhance the value of the service. Although the results of hypothesis testing were not as expected, they definitely showed the unique characteristics of tourism and sharing economy in Airbnb.

5. Conclusion

5.1. Discussion

Smart tourism and the sharing economy within it are now transforming human lives and are a huge innovation in the tourism industry. This change inevitably creates huge resistance. Nevertheless, previous studies on sharing economy have mainly focused on the positive aspects and have paid little attention to negative aspects, such as adoption resistance and potential risks (Ert et al., 2016; Lutz et al., 2018).

In this context, the current study has focused on the risk aspects of sharing economy, which is a social issue. They have investigated how risks affect the development and diffusion of sharing economy. Using EMGB, we attempted to depict the decision-making process of tourists when analyzing sharing economy. We have also examined the various types of perceived risk in sharing economy and their effects on the adoption decision-making process using the well-known sharing economy business, Airbnb. However, the results of this study are quite different from our premise and hypothesis that we can expand the horizon of smart tourism and sharing economy.

First, this study examined the adoption decision process of Airbnb using MGB. As predicted by the theory, attitude, social norm, anticipated emotions, and behavioral control effectively explain desire. Consistent with expectations, desire and intention were also positively and significantly related. Thus, MGB effectively depicts the adoption process of Airbnb for the potential customers.

We also explored the effect of the perceived risks on desire and intention to use Airbnb and found very interesting results. The hypothesis test showed that the financial and privacy risks of Airbnb negatively affect the behavioral intention of potential customers, as expected. However, physical risk and behavioral intention are positively related. Performance risk and desire are also positively related. These findings are contradictory to concerns reported by the media (Bever, 2018; Lieber, 2015; Malhotra & Van Alstyne, 2014) and risk theories in consumer behavior (Cunningham et al., 2005; Quintal et al., 2010; Sönmez & Graefe, 1998).

Fortunately, our results, which conflict with theories and our hypothesis, can be explained from two points of view, namely, disruptive technology theory and the unique characteristics of risk in tourism. According to Guttentag (2015), Airbnb is one of the typical examples of disruptive technology. As an accommodation service, Airbnb has lower performance and service level than a hotel. However, the cost leadership of Airbnb compensates many inconveniences. Some people say that the competitive advantage of Airbnb comes from the cost leadership in the accommodation industry, but this claim is not true. Airbnb offers different values, which cannot be served by the traditional accommodation services through sharing economy. Airbnb allows tourists to meet and play with strangers in the strange destination. Tourists also have opportunities to live in a house full of unique cultures, which cannot be experienced through the standardized service in hotels. Books, furniture, collections, and props in the host's house work as a communication tool and help tourists understand the life and culture of the destination. The location of the host's houses is typically away from the downtown area, which usually takes more time from tourists who use Airbnb than those take the hotel. However, this time lag allows tourists to experience the tourism destination deeply. Airbnb clearly understands this unique selling point and used it frequently in its advertising campaign. Airbnb also constantly improve the service capabilities of hosts to compete with the hotels, which is a well-proven method of the competitive strategy for disruptive innovations.

The second explanation for our results is the unique characteristics of risk in tourism. Tourism is a risk-seeking behavior from the ordinary life. The outcome of the tourism is always uncertain and full of unexpected anecdotes. Even certain leisure activities include life-threatening risk during the play. International tourism inevitably meets an unpleasant moment because of cultural conflicts. Nonetheless, many people make a risky choice because they know the fun inside the risk. Risk is one of the most important factors in the decision process in the tourism. Information selection and decision-making processes of tourists reflect the perceived risk in the process, and the level of risk frequently changes behaviors of tourists during the process. Adventure tourism is not enjoyed by a specific person who prefers the risk but by a generic person who can assess and control the risk within it. If the perceived risk only works negatively in tourism, then tourism cannot be sustainable. Along with the unique characteristics of risk in tourism, the trust mechanisms in sharing economy strengthen the controllability of the perceived risk during the travel. Photos of hosts, various information categories, and reviews enable users to fully assess and evaluate the risk in the decision-making. Information provided by the trust mechanisms can deliver the charming points of hosts’ services in Airbnb and change the perceived risk of Airbnb into the attractive point.

These findings and explanations provide meaningful implications for traditional hospitality industry and sharing economy. The hospitality industry should be aware that competition with sharing economy is different from the usual competitions in the industry. Sharing economy follows the disruptive technology rules, which are quite different from the traditional business practices. Hotels should enhance their service level or develop new values, which cannot be followed by sharing economy. When sharing economy catches up with the service standard of the hotels, the hospitality market will be disrupted instantly.

For sharing economy, our findings give a totally new viewpoint of the perceived risk in the tourism. The perceived risk can be converted into attractiveness. Nowadays, many new businesses are born from the various infrastructure of the smart tourism. If we evaluate these new business based on the risk measures of the traditional business, then we will lose the opportunities to get another Airbnb or Uber. Regulation and supervision of the government in the tourism industry should be performed after the recognition of the unique risk system within the industry. The perceived risk should be controlled rather than eliminated in the tourism industry. The controlled risks in the tourism activities can appeal to users and work as the attractiveness of the destination.

5.2. Limitations

Although this study showed interesting results and insights based on EMGB and perceived risk theories, the interpretation of our analysis has several limitations. First, our survey sample was controlled to the conservative technology users. This study aimed to review the adoption process of the sharing economy, especially Airbnb. Although Airbnb is not popular compared to other countries, most early adopters in Korea who prefer new innovations already experienced the platform during their international travel. To focus on the adoption process, we only focused on potential users who did not experience Airbnb. This focus naturally confines our samples to technological conservatives. To expand our theory, various technological behavioral groups should be considered in the later studies. Also, we used the online panel survey method. Although our online survey was performed by experienced marketing research company Korean Research, the generalization of our result should be approached with caution. Further studies based on large samples and including other countries are required for generalization of results.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ipm.2019.102108.

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