Tourism Management 67 (2018) 224–236

Contents lists available at ScienceDirect

Tourism Management

journal homepage: www.elsevier.com/locate/tourman

Motivations and constraints of Airbnb consumers: Findings from a mixed-methods approach

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HIGHLIGHTS

- We investigate a comprehensive set of motivations and constraints of Airbnb consumers through a mixed-methods design.
- Reconciling the literature and our qualitative findings, we propose and test a conceptual model in a national survey.
- Motivations including price value, enjoyment, and home benefits significantly explain overall attitude toward Airbnb.
- Distrust is the only constraint factor that predicts overall attitude.
- Insecurity and subjective norms such as social influence and trend affinity predict behavioral intentions.

ARTICLE INFO

Article history:
Received 8 January 2018
Accepted 13 January 2018
Available online 22 February 2018

Keywords:
Sharing economy
Airbnb
Motivations
Constraints
Hotel
Tourism

ABSTRACT

Airbnb is widely recognized as a disruptive innovation in the tourism industry. While separate studies have examined various factors affecting consumers' adoption of Airbnb, the literature has largely focused on a handful of factors in isolation. Adopting a sequential mixed-methods approach, this study proposes a comprehensive conceptual model integrating the literature and findings of a qualitative study and subsequently tests the model via a national survey. The results suggest that, for motivations, price value, enjoyment, and home benefits significantly explain overall attitude toward Airbnb. As for constraints, distrust is the only factor that significantly predicts overall attitude, while insecurity is directly related to behavioral intentions. Overall attitude, perceived behavioral control, and subjective norms, such as social influence and trend affinity, predict behavioral intentions. This study contributes to the literature by simultaneously examining the predictive power of both motivations and constraints of Airbnb consumers in explaining overall attitude and purchase behavior.

1. Introduction

The rise of the sharing economy is significantly impacting the tourism and hospitality industry (Zhu, So, & Hudson, 2017). In particular, peer-to-peer business platforms such as Airbnb have emerged as a 'disruptive innovation' enabling consumers to participate in what is termed 'collaborative consumption' in which they jointly share underutilized resources such as cars and rooms (Botsman & Rogers, 2010; Zervas, Proserpio, & Byers, 2014). Collaborative consumption is "a peer-to-peer-based activity of obtaining, giving, or sharing the access to goods and services, coordinated through community-based online services" (Hamari, Sjöklint, & Ukkonen, 2016, p. 3). As one of the most widely cited examples of such consumption model, Airbnb provides an alternative way of renting an accommodation through an online community marketplace and allows short-term rentals of choices of different room types – entire home, private rooms, or shared rooms (Zervas et al., 2014). Airbnb specifically fulfills travelers' needs, such as accommodations with lower prices and opportunities to interact with the local community (Guttentag, 2015). Recent data from Airbnb (2016) show that more than 200 million total guests have used Airbnb, and the company has 10 million bookings and is used by more than 50,000 renters per night (PricewaterhouseCoopers, 2015).

The growing popularity of Airbnb has resulted in an emerging body of literature examining the factors that drive or deter

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https://doi.org/10.1016/j.tourman.2018.01.009

consumers from choosing Airbnb (e.g., Guttentag, 2015, 2016; Tussyadiah, 2015). While in the context of the sharing economy consumers' perceived value is a significant factor in determining their attitude as well as adoption intention toward the innovation (Zhu et al., 2017), adoption of peer-to-peer accommodation could also be motivated by social factors such as social benefits (Tussyadiah, 2016) and social interactions (Guttentag, Smith, Potwarka, & Havitz, 2017). Research shows that price value, community, home atmosphere, sustainability are major factors motivating consumers to choose Airbnb (Guttentag, 2015; Liang, 2015; Tussyadiah, 2015), while distrust, efficacy, unpredictability, and lack of cost savings have been found as constraints for using Airbnb (Liang, 2015; Tussyadiah & Pesonen, 2016a; Tussyadiah, 2015). Furthermore, separate studies found that authenticity (Guttentag et al., 2017), novelty (Guttentag, 2016), social interactions (Stors & Kagermeier, 2015; Tussyadiah, 2015), home benefits (Guttentag, 2016), and trend affinity (Möhlmann, 2015) affected consumers' decision to adopt Airbnb. Other factors such as insecurity, uncertainty or perceived risk (Mao & Lyu, 2017), distrust (Tussyadiah & Pesonen, 2016a), and unfamiliarity (Tussyadiah & Pesonen, 2016a) also seem to play an important role in the same context.

Although these studies have contributed to the early understanding of Airbnb form the consumer perspective, what is lacking is a holistic view of how those reported factors jointly and relatively determine consumers' attitude and other behavioral responses regarding Airbnb. More specifically, prior studies have mainly focused on examining a handful of factors in isolation or ignored their predictive power in explaining consumer related outcomes, without providing a broad perspective on the issue. For example, Guttentag (2016) conducted a motivation-based segmentation study and found that respondents were strongly attracted to Airbnb by practical attributes, and less so by experiential features. However, they did not test any predictive conceptual relationships between motivation and/or constraint factors and theoretically relevant outcome variables. While Tussyadiah and Pesonen (2016a) explored drivers and barriers of peer-to-peer accommodation, only two motivation factors such as social and economic appeals showed relevance to consumer decisions, and the explantory power of these factors was not examined. In a more recent study of why consumers chose Airbnb again, Mao and Lyu (2017) found that unique experience expectations and perceived value positively determined consumer attitude toward Airbnb, whereas perceived risk had a negative effect on such attitude. Their model, however, did not consider several other established motivations such as social interactions, enjoyment, and home benefits and constraints such as distrust. While relevant and contributory, these studies are fragmentary in that they did not capture the full dynamics of how a variety of factors relate to consumers' overall attitude and purchase-relevant behaviors toward Airbnb. Studies providing a more complete account of what drives and deters consumer decisions to adopt Airbnb are in great need for theoretical advances at this point. Such studies will also need to reconcile and integrate various study results in their first step.

This study aims to address the critical paucity in the extant literature by employing a mixed-methods approach with a qualitative study followed by a quantitative national survey. Three specific goals motivated this study. First, the fragmentary results and inconsistent findings from previous studies needed a thorough reexamination and reconciliation to (a) avoid duplicated conceptual efforts in future research and (b) develop a comprehensive but parsimonious set of the motivation and constraint factors for the purpose of building an effective measurement model. A series of focus group interviews were conducted to reaffirm and complement the previous studies, redefine several concepts needing additional refinement and reconciliation, and (re)operationalize these concepts toward greater practical applications. Second, based on the critical review and preliminary qualitative results, this study proposes a conceptual model geared to a more holistic understanding of the motivations and constraints of consumers in choosing peer-to-peer accommodation of Airbnb. Furthermore, to facilitate future theoretical development around the sharing economy, this study examines the relationships between the motivation/constraint factors and purchase-relevant behavioral indicators in the framework of a widely adopted, proven theory, the *theory of planned behavior.* By doing so, this study attempts to add meaningfully to the literature by offering a conceptual framework as well as an integrated view for future investigations into consumers' choice decisions for Airbnb.

1.1. Theoretical background

1.1.1. The theory of planned behavior (TPB)

To investigate consumer motivations and constraints affecting attitudes and behaviors, this study relies on the Theory of Planned Behavior (TPB). The TPB was developed to predict an individual's behavioral intentions toward a specific event (Ajzen, 1985, 1991). Behavioral intention represents an individual's readiness or willingness to behave in a certain way (Ajzen, 1985). The TPB holds that behavioral intention is determined by three antecedents: Attitude, perceived behavioral control, and subjective norms (Ajzen, 1991). TPB posits that the individual's behavioral intention is influenced directly by motivation factors in their decision-making processes (Ajzen, 1991). Empirical studies have found that such motivation factors have predictive power in explaining attitude as well as subsequent behavioral intention (Hsu & Huang, 2010; Lam & Hsu, 2004).

The TPB has been extensively adopted in tourism and hospitality research to understand travelers' behavioral intentions. For example, scholars have used the TPB to study travelers' intentions to stay at green hotels (Chen & Tung, 2014; Han & Kim, 2010; Teng, Wu, & Liu, 2013), to visit a destination (Lam & Hsu, 2006; Quintal, Lee, & Soutar, 2010), to spread negative WOM (Cheng, Lam, & Hsu, 2006), as well as to take a wine-based vacation (Sparks, 2007). Several researchers conceptualized motivation factors as antecedents to the theoretical components of TPB to predict tourists' behavioral intentions (e.g., Chien, Yen, & Hoang, 2012; Hsu & Huang, 2010). As the focus of this study lies in the examination of motivations and constraints of Airbnb consumers, TPB was deemed relevant as a guiding conceptual framework.

1.2. Motivations

1.2.1. Price value

Price value or economic benefits are a main factor driving consumer decisions to use Airbnb. Unlike the summary construct of perceived value, which represents "the consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given up" (Zeithaml, 1988, p. 14), price value is often conceptualized as a value dimension together with emotional value, social value, and quality value (see Sweeney & Soutar, 2001; Walsh, Shiu, & Hassan, 2014). Price value is a cognitive tradeoff between the perceived benefits of the offering and the specific monetary cost for using it (Venkatesh, Thong, & Xu, 2012). Studies show that such monetary value is critical in choosing Airbnb (Guttentag, 2016; Mao & Lyu, 2017; Satama, 2014; Tussyadiah & Pesonen, 2016a; Yang & Ahn, 2016). Similarly, in a recent study examining ridesharing, Zhu et al. (2017) found that consumers' perceptions of value significantly predicted their attitude toward the application. Tussyadiah and Pesonen (2016a) also support the significance of the cost saving features, thereby suggesting that economic appeal is a factor driving consumers' use of peer-to-peer accommodation.

1.2.2. Authenticity

Authenticity is often regarded as fundamental to the Airbnb experience. The concept of authenticity has been extensively applied in the tourism field (e.g., Hughes, 1995; Wang, 1999) to examine tourism experiences or products such as agri-tourism (Daugstad & Kirchengast, 2013) and film tourism (Buchmann, Moore, & Fisher, 2010), as well as heritage (Halewood & Hannam, 2001) and historic districts (Lu, Chi, & Liu, 2015). In the context of Airbnb, authenticity is defined as Airbnb consumers' recognition of 'real' experiences of staying at an Airbnb property (Liang, 2015). The importance of authenticity has been highlighted in a number of prior hospitality studies including Lamb (2011) reporting "authenticity seeking behavior" as a primary driver in using peer-to-peer accommodation. A recent Morgan Stanley Report (Nowak et al., 2015) also found authentic experience to be one of the strongest motivations to use Airbnb. More recently, Poon and Huang (2017) suggest that an authentic local experience is a unique appeal of peer-to-peer accommodation. Therefore, authenticity may serve as an important factor driving consumers' Airbnb decisions.

1.2.3. Novelty

Novelty is generally defined as the degree to which the consumer desires to obtain information about or experience new products (Manning, Bearden, & Madden, 1995). Hirschman (1980) conceptualized novelty-seeking from the consumer's perspective, describing inherent novelty seeking is "conceptually indistinguishable" from inherent innovativeness (p. 285). The notion of novelty seeking is consistent with personal innovativeness, which represents one's tendency to adopt innovations (Guttentag, 2016). Novelty is also conceptually similar to what Mao and Lyu (2017) called unique experience, which is defined as travelers' personal feelings derived from partaking in non-standardized, individually tailored tourist products and services. According to Guttentag (2016), novelty seekers could be drawn to Airbnb because it could provide a more novel travel experience than that of a traditional form of accommodation.

1.2.4. Enjoyment

Enjoyment or fun is a hedonic motivation determining consumers' acceptance of a new product or innovation (Ha & Stoel, 2009). In the technology acceptance literature, hedonic motivations are consumers' fun or pleasure derived from using a new technology (Venkatesh et al., 2012), which drive consumers' new technology acceptance and use (Thong, Hong, & Tam, 2006; Venkatesh et al., 2012). In retail settings, hedonic motivations positively affect the consumer's attitude toward online retail shopping (Childers, Carr, Peck, & Carson, 2001; Ha & Stoel, 2009). Similarly, participation in collaborative consumption activities such as staying at an Airbnb may be an enjoyable experience (Tussyadiah & Pesonen, 2016a). Airbnb users' internal motivations comprise users' enjoyment driven by the activities themselves at Airbnb, which substantiates the role of enjoyment in forming consumer attitude toward Airbnb (Yang & Ahn, 2016).

1.2.5. Home benefits

Home benefits represent functional attributes of a home – 'household amenities,' 'homely feel,' and 'large space" (Guttentag, 2016). Airbnb accommodations provide many benefits similar to those coming from a home environment. Some tourists may prefer the feeling of being home while at a hotel and access to practical residential amenities such as a full kitchen, a washing machine, and a dryer (Guttentag, 2015). In Johnson and Neuhofer's (2017) theoretical framework of value co-creation for Airbnb, a key operant or value co-creation resource is Airbnb home, which is described as a "home away from home" that includes features of a home such as a bedroom and a kitchen. Such home benefits reflect the main physical product that guests obtain through Airbnb. Nowak et al.'s (2015) survey of U.S. and European Airbnb users indicated that having an "own kitchen" was one of the main reasons for choosing Airbnb, emphasizing the significance of home benefits.

1.2.6. Social interactions

Airbnb fosters direct interactions between the host and guest by allowing tourists to connect with local communities and to share their personal experiences. As such, the opportunity for personal interaction plays a major role when choosing to stay at an Airbnb property. For example, vacationers choosing Airbnb would like to get to know new people and to receive travel recommendations from the host (Stors & Kagermeier, 2015). Social appeal of such experience further includes interacting with the host and local people and obtaining insiders' tips on local attractions, which are the benefits of Couchsurfing (Poon & Huang, 2017). Camilleri and Neuhofer (2017) suggest that social practice draws attention to instances where the host and guest spend time interacting with each other. They describe that such interactions include showing guests around, giving them information about local transportation, and taking them to the beach or introducing them to friends. As such, collaborative consumption offered by Airbnb provides opportunities to socially interact with local people as well as the host.

1.3. Constraints

1.3.1. Perceived risk

A commonly cited constraint factor with respect to Aribnb adoption is perceived risk. Perceived risk is defined as uncertainty felt regarding possible negative consequences of consuming a product or service (Featherman & Pavlou, 2003). Kim, Ferrin, and Rao (2008) suggest that the consumer's perceived risk is the belief in possible negative results that would happen from a purchase. Examining ridesharing, Zhu et al. (2017) defined perceived risk as the potential for loss from using such service. They argued that ridesharing application may pose risks associated with not only online booking and transactions but also offline consumption and experience. Mao and Lyu (2017) described perceived risk associated with Airbnb as a subjective expectation of a potential loss when pursuing a desired result. Therefore, perceived risk represents consumers' beliefs in all possible negative results that may happen when using Airbnb.

1.3.2. Distrust

Distrust in the Airbnb business model and the individual host inhibits consumers from choosing Airbnb as an alternative accommodation. Trust represents consumers' willingness to rely on an exchange partner (Moorman, Zaltman, & Deshpande, 1992). Trust in the context of Airbnb means accepting a position of vulnerability and trusting that the exchange partner will fulfill his or her part (Satama, 2014). Olson (2013) found that consumers' perceived fears about participating in the sharing economy were the key barrier to participating in collaborative consumption. Botsman and Rogers (2010) also posit that collaborative consumption means trusting strangers. Distrust is therefore defined for this study as the lack of interpersonal trust between the guest and the host, lack of trust toward technology, and lack of trust toward Airbnb (Tussyadiah & Pesonen, 2016a).

1.3.3. Unfamiliarity

Given that peer-to-peer accommodation is a relatively new consumption model introduced to the tourism industry, consumers may still have limited knowledge about this alternative accommodation. The lack of knowledge or ability to use, therefore, may be perceived as a constraint in adopting peer-to-peer accommodation (Tussyadiah & Pesonen, 2016a). Unfamiliarity is conceptually similar to self-efficacy, which represents one's judgments of one's own capabilities to perform a task (Bandura, 1986). Consumers may avoid tasks that they believe they lack coping capabilities (Bandura, 1982). In the sharing economy, where the product offering is still considered new and innovative, self-efficacy affects consumer attitude toward ridesharing application (Zhu et al., 2017). Efficacy was found to be a main barrier when considering peer-to-peer accommodation rentals, suggesting that an increase in users' familiarity with the platform may reduce the barrier to collaborative consumption (Tussyadiah, 2015).

1.4. Other conceptually relevant factors

The literature also implies the conceptual relevance of several additional theoretical concepts. For example, the TPB literature holds that normative pressures are norms developed through external and interpersonal influences (Ajzen, 1985). Two forms of subjective norms are of particular relevance to the adoption of Airbnb: Social influence and trend affinity. Social influence represents the extent to which the consumer's important others such as friends and family believe he or she should use the focal product or innovation (Venkatesh et al., 2012). Similarly, given that the sharing economy or collaborative consumption model is emerging as a new trend changing consumers' planning and actual travel behavior (Tussyadiah & Pesonen, 2016b), another important form of social norm is trend affinity. Trend affinity occurs when the consumer wishes to follow such a trend or seeks to use innovative and fashionable products and services such as Airbnb (Möhlmann, 2015). However, empirical investigations failed to support its significance in both the contexts of car2Go or Airbnb (Möhlmann, 2015). Additionally, sustainability, which reflects the beliefs that collaborative consumption may reduce the development of new products and the use of raw materials, as well as support the local community and economy, could also affect the consumer's decision to choose Airbnb (Tussyadiah & Pesonen, 2016a). Consumers may feel such sustainable marketplaces can optimize the environmental, social, and economic impacts of consumption in order to better achieve sustainability (Luchs et al., 2011). Related to sustainability is sharing economy ethos, which represent the thinking such as money spent to locals, environmental friendliness, and the philosophy of Airbnb that supports the community's wellbeing (Guttentag et al., 2017). Mao and Lyu (2017) also found the significant effect of word-of-mouth communications on consumer attitude toward Airbnb. Table 1 summarizes factors affecting consumers' attitudes to or adoption of Airbnb.

Table 1
Summary of literature on factors affecting consumer attitudes to or adoption of Airbnb.

Factors	Definitions	Literature
Price value/Economic benefits	The cognitive tradeoff between the perceived benefits of the offering and the monetary cost for using it (Venkatesh et al., 2012).	Tussyadiah and Pesonen (2016a), Satama (2014), Yang and Ahn (2016), Mao and Lyu (2017), and Guttentag (2016)
Authenticity/Local authenticity	The perceptions of Airbnb consumers' cognitive recognition of 'real' experiences of staying at an Airbnb place (Liang, 2015).	Liang (2015), Guttentag et al. (2017), Poon and Huang (2017), and Mody, Suess, and Lehto (2017)
Novelty	The degree to which a consumer desires to obtain information or experiences about new products (Manning et al., 1995).	Guttentag (2016), Johnson and Neuhofer (2017), and Mao and Lyu (2017)
Enjoyment/hedonic motivations	The fun or pleasure a consumer derives from using a product (Venkatesh et al., 2012).	Tussyadiah and Pesonen (2016a) and Satama (2014)
Social interactions/Community	Interacting with the host and local people, and getting insiders' tips on local attractions (Poon & Huang, 2017).	Guttentag (2016), Johnson and Neuhofer (2017), Camilleri and Neuhofer (2017), Poon and Huang (2017), Mody et al. (2017), and Tussyadiah and Pesonen (2016a)
Social influence/Social value	The degree to which a consumer's important others (friends, family etc.) believe he or she should use the product (Venkatesh et al., 2012).	Satama (2014)
Home benefits	Functional attributes of a home – 'household amenities,' 'homely feel,' and 'large space' (Guttentag, 2016).	Guttentag (2016) and Johnson and Neuhofer (2017)
Sustainability	The beliefs that collaborative consumption reduces the development of new products and the consumption of raw materials as well as supports local residents and local economy (Tussyadiah & Pesonen, 2016a).	Tussyadiah and Pesonen (2016a) and Hamari et al. (2016)
eWOM	Personal conversations among consumers about products/services (Sen & Lerman, 2007).	Mao and Lyu (2017)
Sharing economy ethos	The ethos of the sharing economy are money spent to locals, environmental friendliness, and philosophy of Airbnb (Guttentag et al., 2017).	Guttentag et al. (2017)
Familiarity/unfamiliarity	A person's feeling about an entity and is often based on previous interactions, experience and learning regarding the what, who, how and when of what is occurring (Gefen, 2000; Komiak & Benbasat, 2006).	Mao and Lyu (2017) and Tussyadiah and Pesonen (2016a)
Perceived risk	The felt uncertainty regarding possible negative consequences of using a product or service (Featherman & Pavlou, 2003).	Liang (2015), Mao and Lyu (2017), and Tussyadiah and Pesonen (2016a)
Distrust/Lack of trust	Lack of interpersonal trust (guests–hosts), lack of trust toward technology, lack of trust toward the company (Tussyadiah & Pesonen, 2016a).	Tussyadiah and Pesonen (2016a) and Satama (2014)

2. Methods

This study adopted a sequential mixed-methods approach with a qualitative phase followed by a quantitative phase of data collection and analysis to expand on the initial findings (Creswell, Clark, Gutmann, & Hanson, 2003; Tashakkori & Teddlie, 2003). The initial qualitative phase was designed to complement the inconsistent and incomplete results from previous research. The use of qualitative techniques allowed exploring the underlying factors that motivated or constrained consumers in adopting Airbnb. This exploratory stage of research gave rise to a conceptual model to be tested later in the quantitative stage.

2.1. Qualitative method and results

The main technique for obtaining qualitative information was semi-structured focus group interviews with open-ended questions. The lack of qualitative enquiries into the subject matter and the inconsistent previous research findings motivated us to use a qualitative phase to uncover any additional motivators and constraints. Given that the millennials are a large segment of Airbnb (Airbnb, 2016), all interviewees were undergraduate students recruited on campus at a large university on the East Coast of the U.S.. A total of eight focus group interviews were conducted in March 2017, with four having stayed at an Airbnb before and the other four with no prior Airbnb experience. The interviews ended when no new substantive information emerged. The duration of the interviews ranged from 20 to 50 min with an average of approximately 30 min. Upon the respondent's consent, all interviews were digitally recorded.

One of the authors conducted all interviews while taking notes. Participants were asked to discuss their knowledge of Airbnb, the key factors that motivated them to choose to stay at Airbnb (the experience group), and the key factors that affected their decisions to not choose Airbnb as an alternative accommodation (the non-experience group). Interviews were audiotaped and later analyzed separately by two members of the research team. In this phase, themes were derived from both the data (an inductive approach) based on the meaning captured in the content and the researcher's prior theoretical understanding of the phenomenon (an a priori approach) (Ryan & Bernard, 2003). Two researchers verified independently the list of the identified factors for accuracy. The results of the analysis show that factors highlighted in previous research, such as unfamiliarity, sustainability, community, and sharing economy ethos did not appear to be driving consumer choice of Airbnb, while trend affinity and insecurity, which were not previously reported in the literature, were newly found to be critical to Airbnb adoption. We integrated our qualitative findings and the results of the previous studies into a comprehensive, conceptual model of both Airbnb motivations and constraints as shown in Fig. 1.

2.2. Quantitative method

To empirically test the proposed model in Fig. 1, we conducted a quantitative, national online survey in the U.S. by measuring Airbnb consumers' motivations and constraints for using Airbnb accommodation (Creswell et al., 2003). Our data collection was by means of Qualtrics Online Sample. To ensure the appropriateness of the sample, we specifically targeted only individuals who had traveled either domestically or internationally in the past 12 months. A purposive quota sampling method generated a gender-balanced sample size of 500 respondents, with 250 having stayed at an Airbnb property and 250 having never stayed at an Airbnb before, which was geared toward improved generalizability of the results.

Upon agreement to participate, the respondents received information about the research. Only those who indicated that they had traveled away from home in the past 12 months for a night or more qualified to participate in the survey. They were subsequently asked to indicate the city and country that they visited in their most recent trip and the type of accommodation used for the trip. Respondents who used Airbnb were directed to the Airbnb version of

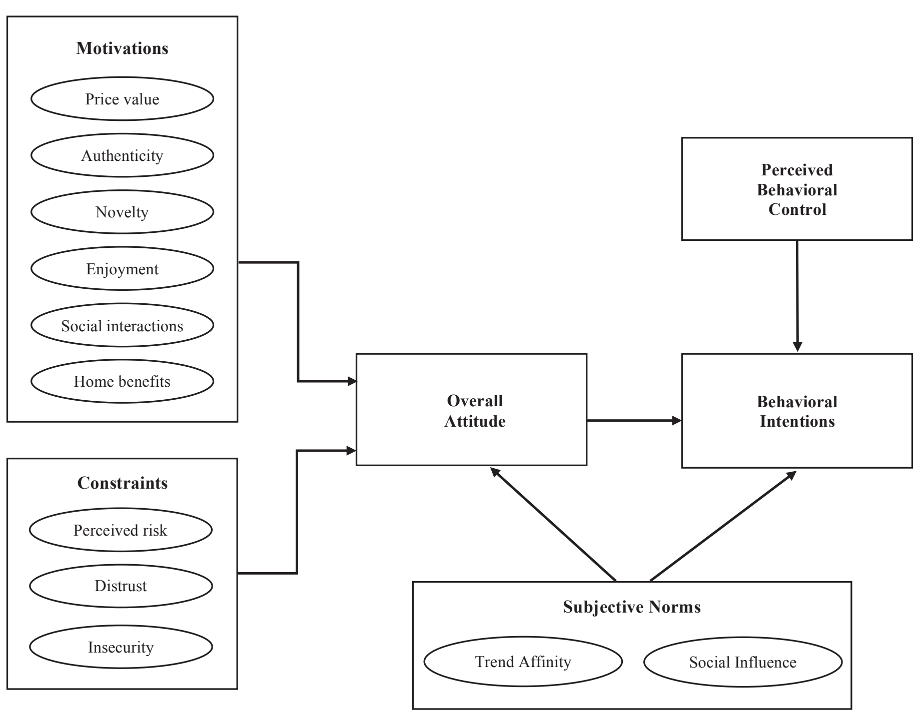

Fig. 1. Proposed conceptual model.

the survey, whereas those who stayed at a typical hotel, model, or timeshare property and had never used Airbnb before taking this most recent trip were directed to the non-user version of the survey. Both groups of respondents were asked to indicate the extent to which they agreed or disagreed with the measurement items. We used a 7-point Likert scale (1 = Strongly Disagree and 7 = Strongly Agree) for all items, with the exception of the overall attitude items for which we used a 7-point sematic differential scale.

In addition, survey research could introduce haphazard responses and lack of attention to survey questions or instructions, which could increase response bias attenuating variable relations or result in a reduced power of analyses, and increase the probability of committing a Type 1 or Type II error. Therefore, we used two attention-checking questions to identify potentially careless responses. Data collection took about four weeks, resulting in a final sample of 519 respondents. As a forced-response option was used, the dataset contained no missing values.

2.3. Measurement instrument

The literature suggested validated scales for use in this study, ensuring initial reliability and validity of our measurement. Specifically, four items originating from Sweeney and Soutar (2001) were adopted from Walsh et al. (2014) to measure price value, while four items from Guttentag et al. (2017) measured authenticity. Four items from Guttentag (2016) captured novelty and three items from Stors and Kagermeier (2015) and Tussyadiah (2015, pp. 817–830) measured social interactions. Three items following Guttentag (2016) measured home benefits, while four items following Möhlmann (2015) and Moeller and Wittkowski (2010) measured trend affinity. Four items borrowed from Nysveen, Pedersen, and Thorbjørnsen (2005), Moore and Benbasat (1991), and Venkatesh et al. (2012) gauged social influence. Four items based on Featherman and Pavlou (2003) measured perceived risk, while insecurity was measured using a scale from Yang, Jun, and Peterson (2004). Two items measuring distrust and two items measuring unfamiliarity were adapted from Tussyadiah and Pesonen (2016a). Four items based on Jeong, Oh, and Gregoire (2003) measured behavioral intentions, and overall attitude was measured using the scale from MacKenzie, Lutz, and Belch (1986). Finally, four items were adapted from Sparks (2007) to measure perceived behavioral control.

3. Results

3.1. Sample profile

The sample included diverse backgrounds. Approximately 56.5% of the respondents were female, while 17% of all respondents were under 30, 62.8% between age 30 and 60, and 20.2% over 60. In terms of annual income levels, 24.9% of the sample earned $40,000 or less, 49.1% between $40,001 and $100,000, and 26% more than $100,000. Regarding the highest education level achieved, 34.3% of the respondents completed undergraduate degrees, 19.3% graduate degrees, 24.9% some college education, 7.9% associate degrees, 12.5% high-school qualified, and 1.2% less than high school.

3.2. Non-response bias

To check for potential non-response bias, we compared early and late respondents on the demographic variables and the individual measurement items (Armstrong & Overton, 1977). The results did not show any significant differences between the first 10% and last 10% of the respondents in terms of sociodemographic characteristics. All measured items were not significantly different ($p > .10$) between the early and late respondents. Based on the results, non-response bias did not appear to be a major issue in this study.

3.3. Partial Least Squares Path Modeling (PLS-PM)

The predictive power of the motivation and constraint factors was tested using Partial Least Squares Path Modeling (PLS-PM). Unlike the classical covariance-based structural equation modeling method that has a primary goal of theory testing and confirmation as well as comparison of alternative theories (Hair, Hult, Ringle, & Sarstedt, 2013), PLS-PM explains at best the residual variance of the latent variables and therefore its goal is to predict key constructs (Fornell & Bookstein, 1982; Hair et al., 2013). As this study investigates the effects of a number of motivation as well as constraint factors on consumer attitude and behavioral intentions toward Airbnb, the focus of our investigation lies in the evaluation of a set of predictive relationships rather than theory testing or confirmation (see Chin & Newsted, 1999; Sarstedt, Ringle, & Hair, 2014). Moreover, an absence of strongly established or widely adopted theories in the fledgling sharing economy literature made it difficult to impose any expected theoretical structure among the variables under our investigation. As such, PLS-PM was selected as an appropriate analytical technique for our data analysis in this study. We followed a two-step process, which involved separate assessments of the outer model and the inner model (Hair et al., 2013). We used SmartPLS 3.0.

3.3.1. Outer model

Assessment of the outer model involves evaluation of the validity and reliability of the construct measures. We first evaluated convergent validity through the strength and significance of the loadings and the average amount of variance extracted (AVE) (Bagozzi & Heatherton, 1994). The results showed that with the exception of one item, which had a loading below the minimum acceptable level of 0.60 (i.e., PBC2), all item loadings exceeded 7.0 (Hair, Black, Babin, Anderson, & Tatham, 2006). After a careful review of the low loading item, it was removed from further analysis and the overall outer model was re-estimated. The results indicate that all items exceeded 0.70. The bootstrap critical ratios of the indicators were statistically significant at $p < .001$ and all AVEs were greater than 0.50 (Fornell & Larcker, 1981), providing strong evidence for the convergent validity of the constructs. Table 2 presents the results.

To check discriminant validity, we adopted three separate approaches (Hair et al., 2013; Henseler, Ringle, & Sarstedt, 2015). First, as our analysis adopted variance-based SEM, we used the newly developed procedure of the heterotrait-monotrait ratio of correlations (HTMT) to check discriminant validity (Henseler et al., 2015). The results indicate that the constructs of authenticity and novelty had a value of 0.898, suggesting discriminant issue (Henseler et al., 2015). On this basis, as well as both constructs capture the notion of new, unique, and non-standard experience, novelty was removed from all further analysis. The outer model was re-estimated and all the previously discussed thresholds were achieved. Second, we examined the item cross-loadings of the indicators (Hair, Ringle, & Sarstedt, 2011). The results show that no item cross-loaded higher on another construct than on their own construct, thereby satisfying discriminant validity (Hair et al., 2013). Second, we used a more conservative approach (Fornell & Larcker, 1981), whereby the square root of the AVE of the constructs was compared to the inter-construct correlations. In each case, the square root of the AVE was greater than the inter-construct correlations, providing evidence of discriminant validity (Chin, 1998; Fornell & Larcker, 1981), as

Table 2
Results summary for the outer model.

Latent Variable/Indicators	Loadings	Critical Ratios	Mean	SD	rho_A	AVE
Price value					0.94	0.84
PV1. Airbnb accommodations are reasonably priced.	0.91	58.58	5.21	1.32		
PV2. Airbnb offers value for money.	0.93	100.47	5.24	1.30		
PV3. Airbnb offers a good product for the price.	0.92	85.60	5.25	1.29		
PV4. Airbnb accommodations are economical.	0.90	67.90	5.23	1.31		
Authenticity					0.92	0.72
AUT1. Airbnb tends to provide an authentic local experience.	0.88	57.63	5.15	1.35		
AUT2. Airbnb tends to offer a unique, one-of-a-kind experience.	0.88	68.26	5.15	1.38		
AUT3. Airbnb tends to provide an opportunity to stay in a less standardized accommodation environment.	0.83	32.12	5.35	1.38		
AUT4. Airbnb tends to offer an accommodation that integrates local cultures.	0.87	46.16	5.20	1.30		
Enjoyment					0.93	0.87
ENJ1. Staying at Airbnb is fun.	0.94	124.12	5.04	1.44		
ENJ2. I would enjoy using Airbnb.	0.95	203.69	5.15	1.53		
ENJ3. Airbnb offers an entertaining accommodation experience.	0.91	62.55	4.98	1.43		
Social interactions					0.88	0.80
SINT1. Airbnb offers guests opportunities to interact more directly with local people.	0.88	66.99	4.59	1.59		
SINT2. Airbnb offers guests opportunities to interact more with other guests.	0.89	70.69	4.09	1.67		
SINT3. Airbnb offers guests good social opportunities with the host.	0.92	94.82	4.50	1.59		
Home benefits					0.95	0.86
HB1. Airbnb offers spacious accommodation like homes.	0.90	73.07	5.37	1.38		
HB2. Airbnb provides guests with home-like amenities.	0.94	105.93	5.49	1.32		
HB3. Airbnb provides a "homely" feel during the stay.	0.94	126.29	5.39	1.37		
HB4. Guests can feel home and relax at Airbnb.	0.93	121.34	5.31	1.43		
Perceived risk					0.96	0.83
PR1. Whether Airbnb offers the money's worth is uncertain.	0.87	48.61	4.16	1.60		
PR2. Whether Airbnb offers expected quality is uncertain.	0.94	133.55	4.12	1.63		
PR3. Whether Airbnb offers guests a good image is uncertain.	0.90	60.06	4.04	1.58		
PR4. Whether Airbnb offers a good overall lodging experience is uncertain	0.93	77.39	4.07	1.67		
Insecurity					0.96	0.86
INS1. Airbnb may not provide a high level of security of guests' personal information.	0.89	58.18	4.05	1.61		
INS2. Airbnb cannot be trusted to provide a high degree of guest safety.	0.93	87.95	3.83	1.67		
INS3. Staying at Airbnb means I may not be in safe hands.	0.95	129.66	3.77	1.68		
INS4. Transactions with Airbnb may not be safe and secure.	0.94	121.50	3.67	1.70		
Distrust					0.94	0.94
DIST1. I do not trust the Airbnb business model.	0.97	227.08	3.04	1.65		
DIST2. I do not trust the online business transactions with Airbnb.	0.97	209.68	3.07	1.61		
Trend affinity					0.93	0.82
TA1. Airbnb-style accommodation is a new fad I feel I should use.	0.86	60.12	4.58	1.73		
TA2. People will see me as trendy if I use Airbnb.	0.91	74.25	4.27	1.69		
TA3. Staying at Airbnb will present me as contemporary.	0.93	116.82	4.42	1.62		
TA4. Using Airbnb is one way of showing that I follow the current accommodation trend.	0.91	86.54	4.38	1.68		
Social influence					0.94	0.82
SINF1. People like me would use Airbnb.	0.85	75.14	3.79	1.79		
SINF2. Using Airbnb would improve my image among my friends and peers.	0.90	86.73	3.91	1.74		
SINF3. People who are important to me probably think that I should use Airbnb.	0.93	123.91	3.81	1.84		
SINF4. My friends and peers would expect me to use Airbnb.	0.92	111.41	3.79	1.79		
Perceived behavioral control					0.85	0.70
PBC1. I can afford staying at an Airbnb if I want.	0.70	18.21	5.46	1.37		
PBC2. Few things prevent me from using Airbnb. (DELETED)	NA	NA	NA	NA		
PBC3. I have enough knowledge or experience to use Airbnb.	0.90	89.87	4.70	1.89		
PBC4. Using Airbnb is as convenient as using other typical hotels.	0.89	102.74	4.82	1.57		
Overall attitude					0.97	0.95
OA1. Airbnb is…1 = Bad…7 = Good	0.98	297.77	5.43	1.57		
OA2. Airbnb is…1 = Unpleasant…7 = Pleasant	0.97	206.19	5.45	1.57		
OA3. Airbnb is…1 = Unfavorable…7 = Favorable	0.98	246.41	5.42	1.59		
Behavioral intentions					0.94	0.84
BI1. I will use Airbnb in the near future.	0.94	143.57	4.80	1.82		
BI2. Airbnb will be one of the accommodation options I will consider for my next trip.	0.95	170.52	4.95	1.81		
BI3. I would recommend Airbnb to others as a viable lodging option.	0.94	154.07	4.89	1.79		
BI4. I would like to invest more time to learn about Airbnb as I would like to stay there on some of my future trips.	0.82	38.53	4.86	1.62		

Note: Results were based on bootstrapping with 5000 subsamples; SD = standard deviation; AVE = average variance extracted; rho_A = Dillon-Goldstein's rho.

shown in Table 3.

Construct reliability was assessed via internal consistency and indicator reliability (Hair et al., 2013). Internal consistency was evaluated with Dillon-Goldstein's (or Jöreskog's) rho, which does not assume that each manifest variable has equal importance in defining the latent variable (Chin, 1998). Such an estimate is generally interpreted in the same way as Cronbach's alpha. As Table 2 shows, all factors achieved the satisfactory level of 0.70 or higher for reliability (Hair et al., 2006; Nunnally & Bernstein, 1994). Combined, all these tests on the outer model demonstrated that the measurement scales were valid and reliable for measuring the proposed constructs.

3.3.2. Inner model

The proposed inner model was evaluated through an examination of path coefficients between the exogenous and endogenous

Table 3
Discriminant Validity Analysis based on Fornell-Larcker Criterion.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Overall attitude	**0.97**												
2. Authenticity	0.69	**0.85**											
3. Perceived behavioral control	0.69	0.69	**0.84**										
4. Behavioral intentions	0.84	0.69	0.75	**0.91**									
5. Distrust	−0.49	−0.37	−0.39	−0.48	**0.97**								
6. Enjoyment	0.81	0.76	0.71	0.84	−0.45	**0.93**							
7. Home benefits	0.73	0.75	0.64	0.70	−0.40	0.80	**0.93**						
8. Insecurity	−0.30	−0.14	−0.17	−0.31	0.66	−0.24	−0.20	**0.92**					
9. Perceived risk	−0.28	−0.08	−0.18	−0.27	0.58	−0.22	−0.19	0.80	**0.91**				
10. Price value	0.66	0.75	0.71	0.67	−0.37	0.70	0.68	−0.17	−0.13	**0.91**			
11. Social influence	0.67	0.63	0.63	0.76	−0.34	0.77	0.60	−0.18	−0.14	0.55	**0.90**		
12. Social interactions	0.63	0.70	0.59	0.65	−0.28	0.75	0.70	−0.12	−0.08	0.63	0.68	**0.90**	
13. Trend affinity	0.65	0.64	0.57	0.72	−0.28	0.74	0.62	−0.14	−0.09	0.56	0.86	0.70	**0.90**

Note: The bold-faced diagonal elements are the square root of the variance shared between the constructs and their measures. The off-diagonal elements are the correlations between constructs.

Table 4
Results of the inner model path coefficients.

Hypothesis and Path	Path Coefficients	Standard Errors	Critical Ratios	p Values	f^2	90% Confidence Intervals
Direct effects						
Overall attitude -> Behavioral intentions	0.33	0.049	6.57	.000	0.166	[0.249, 0.410]
Authenticity -> Overall attitude	0.04	0.052	0.77	.221	0.002	[−0.043, 0.128]
Authenticity -> Behavioral intentions	−0.02	0.043	0.46	.323	0.001	[−0.090, 0.052]
Perceived behavioral control -> Behavioral intentions	0.19	0.039	4.78	.000	0.072	[0.125, 0.254]
Distrust -> Overall attitude	−0.11	0.036	2.97	.001	0.018	[−0.166, −0.048]
Distrust -> Behavioral intentions	−0.03	0.027	0.99	.162	0.002	[−0.070, 0.018]
Enjoyment -> Overall attitude	0.45	0.057	7.81	.000	0.136	[0.352, 0.541]
Enjoyment -> Behavioral intentions	0.28	0.056	5.04	.000	0.078	[0.194, 0.379]
Home benefits -> Overall attitude	0.15	0.051	2.97	.002	0.024	[0.069, 0.238]
Home benefits -> Behavioral intentions	−0.04	0.046	0.77	.221	0.002	[−0.111, 0.039]
Insecurity -> Overall attitude	0.00	0.050	0.08	.468	0.000	[−0.079, 0.086]
Insecurity -> Behavioral intentions	−0.08	0.037	2.12	.017	0.011	[−0.143, −0.020]
Perceived risk -> Overall attitude	−0.06	0.054	1.19	.118	0.005	[−0.156, 0.023]
Perceived risk -> Behavioral intentions	0.02	0.033	0.62	.266	0.001	[−0.031, 0.075]
Price value -> Overall attitude	0.11	0.052	2.18	.015	0.017	[0.034, 0.206]
Price value -> Behavioral intentions	0.03	0.042	0.78	.218	0.002	[−0.036, 0.102]
Social influence -> Overall attitude	0.08	0.050	1.68	.047	0.005	[0.001, 0.165]
Social influence -> Behavioral intentions	0.17	0.046	3.69	.000	0.034	[0.097, 0.248]
Social interactions -> Overall attitude	−0.04	0.035	1.13	.129	0.002	[−0.097, 0.019]
Social interactions -> Behavioral intentions	−0.05	0.031	1.58	.057	0.005	[−0.103, 0.002]
Trend affinity -> Overall attitude	0.05	0.045	1.23	.109	0.002	[−0.015, 0.133]
Trend affinity -> Behavioral intentions	0.08	0.048	1.78	.038	0.009	[0.010, 0.167]
Indirect effects						
Authenticity -> Behavioral intentions	0.01	0.017	0.76	.223	NA	[−0.015, 0.042]
Distrust -> Behavioral intentions	−0.04	0.014	2.52	.006	NA	[−0.059, −0.014]
Enjoyment -> Behavioral intentions	0.15	0.030	4.77	.000	NA	[0.102, 0.202]
Home benefits -> Behavioral intentions	0.05	0.019	2.54	0.006	NA	[0.021, 0.085]
Insecurity -> Behavioral intentions	0.00	0.017	.08	.468	NA	[−0.028, 0.026]
Perceived risk -> Behavioral intentions	−0.02	0.016	1.28	.100	NA	[−0.046, 0.008]
Price value -> Behavioral intentions	0.04	0.018	2.00	.023	NA	[0.010, 0.071]
Social influence -> Behavioral intentions	0.03	0.017	1.57	.058	NA	[0.001, 0.057]
Social interactions -> Behavioral intentions	−0.01	0.012	1.11	.134	NA	[−0.032, 0.006]
Trend affinity -> Behavioral intentions	0.02	0.015	1.19	.117	NA	[−0.005, 0.045]

Note: Results were based on bootstrapping with 5000 subsamples; CI = confidence intervals; NA = f^2 is not provided for indirect effects; all estimates were based on a one-tailed test; for bootstrapping with one-tailed test, SmartPLS produces the 90% confidence internals.

variables, bootstrap critical ratios, coefficient of determination R^2, f^2 effect size, and predictive relevance Q^2 (Hair et al., 2013). Table 4 presents the results. First, we evaluated the significance of the expected relationships between the constructs. According to Kock (2015), when testing relationships in PLS-PM, a one-tailed test is recommended if the coefficient is assumed to have a known or expected directionality (positive or negative). Based on the literature discussed, we relied on a one-tailed test to examine each of the relationships. To test whether path coefficients differed significantly from zero, t values and the associated p-values were calculated based on bootstrapping with 5000 subsamples. The results of the analysis suggest that, of all the paths tested in the model, 11 were supported at $\alpha = 0.05$. Specifically, in terms of motivations, price value ($\beta = 0.11$, $t = 2.18$, $p < .05$), enjoyment ($\beta = 0.45$, $t = 7.81$, $p < .001$), and home benefits ($\beta = 0.15$, $t = 2.97$, $p < .001$) significantly explained overall attitude toward Airbnb, whereas only one constraint, distrust ($\beta = -0.11$, $t = 2.97$, $p < .001$), significantly predicted overall attitude. Social influence ($\beta = 0.08$, $t = 1.68$, $p < .05$) also significantly explained attitude. In addition, insecurity ($\beta = -0.08$, $t = 2.12$, $p < .05$), subjective norm factors including social influence ($\beta = 0.17$, $t = 3.69$, $p < .001$) and trend affinity ($\beta = 0.08$, $t = 1.78$, $p < .05$), overall attitude ($\beta = 0.33$, $t = 6.57$,

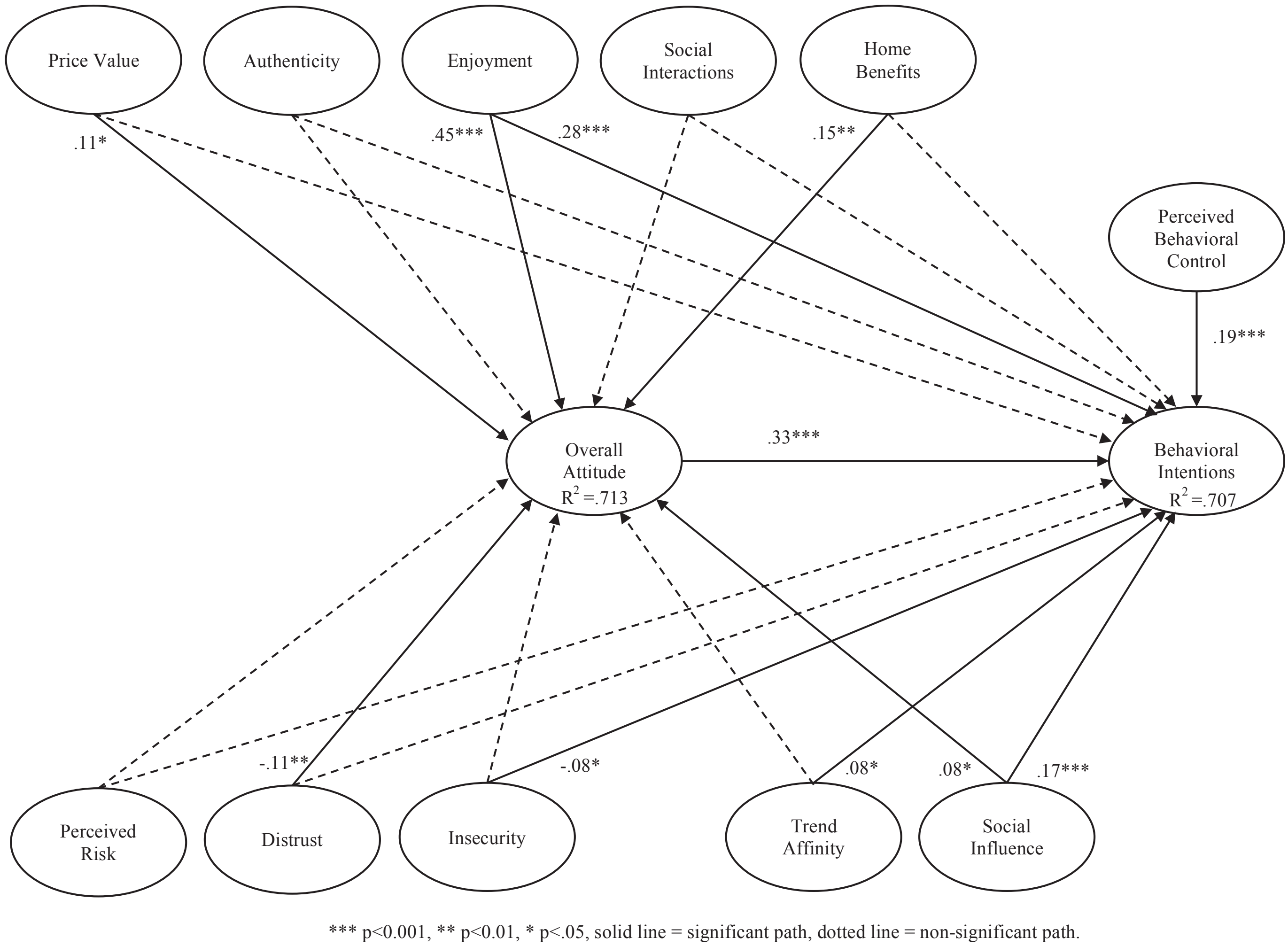

Fig. 2. Results of the Inner Model. ***p < .001, **p < .01, *p < .05, solid line = significant path, dotted line = non-significant path.

$p < .001$), and perceived behavioral control ($\beta = 0.19$, $t = 4.78$, $p < .001$) significantly predicted behavioral intentions.

Second, as the primary objective of PLS-PM is prediction, the most important criterion for the assessment of the goodness of a model is R^2 (Ringle, Sarstedt, & Mooi, 2010). As Fig. 2 indicates, the R^2 values for all endogenous variables exceeded the 0.26 value suggested by Cohen (1988) as indicating sound predictive power of the model. We used Cohen's (1988) guidelines that the f^2 effect size of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively, of the predictor variables. Table 4 shows that all significant exogenous latent constructs have effect sizes ranging from small to large, with the exception of one path (i.e., Distrust → Overall Attitude).

Third, we used the blindfolding procedure to generate the cross-validated redundancy measure Q^2 (Stone–Geisser test) (Geisser, 1974; Stone, 1974). According to Hair et al. (2013), the Q^2 value greater than zero implies that the exogenous construct has predictive relevance to the endogenous construct in the paired relationship. The Q^2 values of the endogenous latent constructs all exceeded zero, with 0.636 for overall attitude and 0.644 for behavioral intentions, thus indicating the model's high predictive relevance for the outcome variables. Overall, the results support the predictive power of the paths, thereby substantiating the structural soundness of the proposed model. Fig. 2 presents the results.

4. Discussion and implications

Several significant findings emerged from this study for future theoretical development efforts in the sharing economy literature. First, building on the literature, we reconciled the findings from previous research and generated additional insights based on the results from the qualitative phase of our mixed-methods study. Factors such as unfamiliarity, sustainability, community, and sharing economy ethos that were previously reported to be influential did not appear to be driving consumer choice of Airbnb, while trend affinity and insecurity were newly found to be significant factors. As a result, we proposed the unprecedented conceptual model that simultaneously captured Airbnb motivations and constraints and showed how these factors served determining attitudinal and behavioral responses.

4.1. Theoretical implications

The empirical results of the model contribute significantly and meaningfully to the literature by synthesizing the piecewise findings from prior research and providing a new framework to understand more completely the drivers and deterrents of the consumer's adoption of Airbnb. In addition to integrating diverse, relevant concepts documented in the literature, our proposed model (a) improved the face validity of the reported results by newly adding trend affinity and insecurity based on our qualitative study, (b) simultaneously tested a comprehensive set of motivations and constraints, and (c) enhanced the practical applicability of the results by presenting a set of refined, both conceptually and empirically, and parsimonious measures.

Our model also proposed a basic theoretical framework to assess relative predictive ability of various Airbnb motivations and constraints. For example, the results show that price value, enjoyment, and home benefits were influential in determining how consumers perceived Airbnb as an alternative accommodation. Specifically, in contrast to Hamari et al.'s (2016) study that showed that economic benefits had no significant influence on attitude toward collaborative consumption, our findings demonstrated the significant effect of price value, thus reinforcing previous research suggesting that low prices (Tussyadiah, 2015), economic benefits (Yang & Ahn, 2016), or perceived value (Mao & Lyu, 2017) motivated travelers to choose Airbnb. Another example is Guttentag et al.'s (2017) study reporting the importance of local authenticity as a consumer motivation to use Airbnb, but our study showed that, when authenticity is considered together with other motivation and constraint factors in the same model, its effect in forming attitude or behavioral intentions appeared relatively insignificant. Unlike many previous studies that reported the zero-order importance of various variables as either an Airbnb motivation or constraint, our study compared these variables' relative importance or predictive power through PLS-PM.

Enjoyment and home benefits emerged in our study as motivations that were relatively important to Airbnb choice. Although Tussyadiah and Pesonen (2016a) reported enjoyment as a insignificant motivation, our data showed that enjoyment significantly explained overall attitude and behavioral intentions. Our findings are largely consistent with previous works in the Airbnb (Satama, 2014; Yang & Ahn, 2016) and collaborative consumption (Hamari et al., 2016) literature. The literature lacks studies establishing the importance of home benefits to Airbnb selection, whereas our study found home-like room facilities or environment to be critical to consumer decisions to choose Airbnb, thus lending support for Guttentag et al. (2017). Given the generally known fact that Airbnb provides a home-like lodging condition, it is intuitive that home benefits may play a meaningful role in Airbnb marketing.

The relative importance of social interaction appeared to be negligible in our data. Tussyadiah (2015) and Botsman and Rogers (2010) highlighted the significance of social motivations in collaborative consumption—a desire to get to know others and interact and connect with local communities—but our data showed that social interactions became an insignificant motivator when it is considered simultaneously with other important and potentially competing motivations in the same model. Besides the relatively low importance of social motivations, this finding could also reflect an increasing trend in the Airbnb context where more and more consumers are renting the entire house or unit rather than sharing with others, which reduced the importance of interacting with others during the say.

In general, constraint variables also resulted in mixed findings between previous studies and our study in which we newly assessed the relative role of these variables together with that of motivation and other constraint variables. For example, while some previous studies supported the negative effect of perceived risk on attitude (Mao & Lyu, 2017) and repurchase intention (Liang, 2015), our data revealed that perceived risk had no significant relationship, in a relative sense, to attitude or behavioral intentions. What became relatively critical in consumer attitude formation, however, was distrust. Distrust appeared in our study as a single most important obstacle negatively affecting consumers' overall attitude toward Airbnb. Although prior research examining distrust is very limited, our results generated new insights supporting the theoretical relevance of trust (or distrust) to Airbnb buying behavior. Our findings are in line with Tussyadiah and Pesonen (2016a), who found distrust to be a key barrier to Airbnb adoption. Furthermore, while previous research on Airbnb has ignored the critical role of a secure accommodation environment, our results suggest that consumers' perceived insecurity of Airbnb accommodation undermined purchase-related responses.

Building on the literature (Mao & Lyu, 2017; Zhu et al., 2017), this study also found that subjective norm factors such as social influence and trend affinity affected the consumer's behavioral intentions. Such findings are consistent with Mao and Lyu (2017)'s study in that subjective norm has a positive influence on attitude. However, they did neither clarify nor test which type of subjective norms exerted the influence. Our study filled this literature gap by investigating the effects of different types of subjective norms (e.g., social influence and trend affinity). Our findings demonstrated the crucial role these social norms play in determining consumers' intentions to adopt Airbnb.

Although the attitude-behavioral intentions relationship is well established in the general context of attitude theory (Ajzen, 1985, 1991), our results presented in Table 3 and Fig. 2 show that overall attitude meditated the effects of several variables toward behavioral intentions, such as price value, enjoyment, home benefits, and distrust. In particular, variables such as price value, home benefits, and distrust had no direct effect on behavioral intentions, while they were still indirectly related to behavioral intentions (see Table 4). Our results are generally compatible with the positive attitude-repurchase intentions relationship as reported by Mao and Lyu (2017) and Zhu et al. (2017) and the attitude-mediated effects of expectations, perceived value, and perceived risk on repurchase intentions, as reported by Mao and Lyu (2017). In addition, we found a significant positive effect of social influence on behavioral intentions. One inconsistent result, however, was the significant positive effect of PBC on behavioral intentions in our study as compared to the insignificant effect in Mao and Lyu's (2017) study.

4.2. Practical implications

Our findings entail several practical implications for industry. One distinct benefit our study offers to industry practitioners is the comprehensive examination integrating the majority of recent studies on how Airbnb consumers adopt (or do not adopt) such a lodging innovation. Few previous studies provided such a collective view of both motivation and constraint factors affecting consumer decisions to choose Airbnb in a single framework. Hence, our conceptual effort provided a 'big' picture of how Airbnb consumers arrive at choosing (or not choosing) Airbnb for their trip. Moreover, our analytic effort provided a holistic assessment of the role of each motivation and constraint factor. When marketers consider each motivation and constraint variable singly, each variable may exhibit its predictive relevance to purchase intention, which may dictate marketers to consider all variables in their marketing programs. One critical question in this case is whether marketers should allocate an equal amount of resource to each variable. By assessing the importance of each variable through a single PLS-PM model, we attempted to shed lights on each variable's comparative importance in predicting purchase intentions. One striking outcome from our simultaneous modeling was the demonstration that such widely believed influential factors as authenticity and social interactions failed to show their relative significance, the finding that weakens previous arguments as well as the widely held belief about the importance of authenticity and social interactions in Airbnb selection. Accumulation of research findings like this will eventually assist marketers in allocating scarce resources more effectively and competitively.

Another notable usage of our study relates to a practical tool to measure both consumer motivations and constraints for Airbnb choice. Coupled with our comprehensive conceptual effort to synthesize fragmentary research findings, our study also provides a set of reliable, practically concise measurement scales that are readily applicable to industry's marketing designs. Our proposed measurement scales are not only based on broadly adopted, previously evaluated sources but also grounded in our empirical reaffirmation of their reliability and validity with fresh, national Airbnb data. Thus, our study may serve as a practical reference for practitioners as well as researchers when developing programs and strategies to manage Airbnb consumers' needs and decision process.

Additional practical implications include some specific aspects of our results. For example, the significant effects of enjoyment, home benefits, and price value suggest that, in the peer-to-peer accommodation sector, developing a value for money product that offers an enjoyable accommodation experience and a home-like environment is of paramount significance. Factors arising from the social environment, such as following a social trend and perceiving peer influence, could also affect consumers' intentions to adopt Airbnb. Finally, distrust was found to be the only constraint factor significantly impacting consumers' overall attitude. This finding highlights a need for individual hosts of peer-to-peer accommodation as well as platform companies such as Airbnb to establish trust with consumers through not only better quality assurance or satisfaction guarantee mechanisms, but also a consistent provision of superior accommodation experiences that exceed expectations. As in the traditional lodging industry, trust-based consumer relations in addition to delightful accommodation experiences beyond expectations are likely to generate positive referrals and word-of-mouth communications.

5. Limitations and future research

In evaluating the significant findings from this study, several limitations need to be acknowledged. First, as our study was based on a sample drawn from an online consumer panel, the findings cannot be generalized to all travelers. Future research could sample consumers from different countries or cultures to determine whether the model is equally valid and useful in other research settings. Similar considerations must be given to the issue of familiarity that may form different impressions about the favorability of Airbnb. Consumers with first-hand experiences with Airbnb may have formed different attitudes and behavioral intentions compared to those without any prior Airbnb experience. Future research should address how such direct experience affects the roles of motivations and constraints in forming purchase intention.

Second, this research used a cross-sectional design and, as such, the predictive relationships found among the constructs do not warrant strong causal inferences. Relying on a widely adopted and proven theory such as TPB is not exempted from the necessity of causal research designs in order to make strong causal inferences. In future research, adoption of an experimental design may allow researchers to better infer cause-and-effect relationships and strengthen the validity of the relational findings. Similarly, an experimental design can be used to examine potential conditions under which Airbnb is more likely to be selected than a traditional accommodation type.

Third, the use of quota sampling could have affected sample representativeness. Future research could define the population of Airbnb consumers more clearly and draw a sample better representative of the population. Broadening the sampling frame is equally necessary in the qualitative research phase we employed in this study. Our student sample for the preliminary interview study could limit our ability to capture a complete picture of both Airbnb motivations and constraints, although our thorough review of previous studies could complement the qualitative study results.

Finally, future studies could also test the proposed model across multiple meaningful demographic or consumer subgroups as well as to assess potentially unobserved heterogeneity in the population. As Airbnb is still a relatively new form of accommodation that is not completely familiar to consumers and as the industry's operational standards are not yet stabilized across properties, consumer opinions are likely to vary often by groups based on unknown referents. Thus, there may exist many unobserved subgroups of opinions about Airbnb. Clearly, additional understanding of this growing sector and its new consumers is necessary through future research so as to continuously refine both product offerings and management practices.

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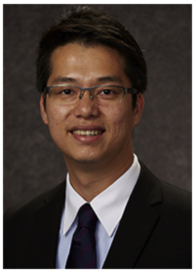

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