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Determinants of the continuance intention of Airbnb users: Consumption values, co-creation, information overload and satisfaction

Abstract
This study examines the relationships among the dimensions of consumption values (functional, social and emotional), co-creation, information overload, satisfaction and continuance intention derived from the use of the Airbnb platform. The researchers conducted a web-based survey among Italians and obtained a valid sample of 259 persons for data analysis. The survey results indicated that only functional value and emotional value are strong predictors of satisfaction in using the Airbnb website for accommodation booking. Co-creation and absence of information overload also contribute to satisfaction in using the Airbnb website for accommodation booking, and satisfaction in turn affects continuance intention. This study contributes to a deeper understanding of users’ continuance intention with regards to the Airbnb website by exploring the possible determinants. Managerial implications include recommendations for hosts to emphasise their prices when listing accommodations on the Airbnb website and to focus on active interaction with potential guests. Information on the website should also be organised to avoid information overload. The study concludes with a discussion of limitations and an indication of future research directions.

Keywords: Airbnb; consumption values; co-creation; information overload; continuance intention; Italy

1 Introduction

Vacationers make their decisions both during the pre-trip planning phase and in situ (Sthapit, 2018a). They may make some of these decisions, which strongly influence their on-site experiences (Hospers, 2009), months before actually embarking on vacation (Sthapit, Kozak, & Coudounaris, 2017). For example, studies have indicated that travellers establish their choice of accommodation early in the trip planning process (Fesenmaier & Jeng, 2000; Hyde, 2004; Woodside & King, 2001). From a demand perspective, Fesenmaier and Jeng’s study (2000) reveals that the choice of accommodation is made in the early stage of planning, together with destination, time and duration of the trip, travel companion, travel route, and overall travel budget. On the supply side, accommodation is a fundamental element of tourism products (Sharpley, 2000) and accounts for an important share of total tourism spending (Losada, Alén, Nicolau, & Domínguez, 2017). However, most research regarding accommodation is limited to those hotel attributes that influence tourists’ accommodation decisions (Sohrabi, Vanani, Tahmasebipur, & Fazli, 2012; Stringam, Gerdes, & Vanleeuwen, 2010). In addition, shifts in current consumption behaviour in the tourism sector and the emergence of a new forms of accommodation, shared peer-to-peer (P2P) hosting, have changed the tourist consumer profile (Ert, Fleischer & Magen, 2016; Fang, Ye & Law, 2016; Tussyadiah & Pesonen, 2015). Customers (tourists) today rely heavily on online and mobile technologies in their pre-trip information gathering and decision-making processes (Choi, Fowler, Goh & Yuan, 2016; Im & Hancer, 2017; Pabel & Prideaux, 2016; Xiang & Gretzel, 2010; Xiang, Gretzel & Fesenmaier, 2009).

‘Sharing economy’ is an umbrella term that covers the sharing of consumption through online platforms (Hamari, Sjöklint, & Ukkonen, 2016; Sthapit & Björk, 2019a). In the tourism sector, the sharing economy connects individuals who have excess property capacity with tourists who require accommodation using an online platform maintained by a third-party company (Botsman & Rogers, 2010). Airbnb, founded in 2008, is the world’s largest accommodations provider in the sharing economy (Leung, Xue, Wen, 2019; Mody, Suess, &
Lehto, 2019; Oskam & Boswijk, 2016) and is the most popular sharing economy platform in the accommodation sector (Guttentag, 2015; Sthapit & Jiménez Barreto, 2018a). Airbnb has emerged as a ‘disruptive innovation’, enabling consumers to participate in what is termed ‘collaborative consumption’, wherein they share underutilised resources, such as cars and rooms (Botsman & Rogers, 2010). Airbnb has become a key competitor of not only other online travel agents (OTAs; e.g., TripAdvisor, Expedia, Travelocity) but also traditional hotels (Wang & Jeong, 2018).

Recent studies have examined value co-destruction in the contexts of Airbnb (Sthapit, 2018b; Sthapit & Jiménez Barreto, 2018b), memorability (Sthapit & Jiménez Barreto, 2018a), sharing (Sthapit & Jiménez Barreto, 2018c), social interactions (Guttentag, Smith, Potwarka, & Havitz, 2018; Lin, Fan, Zhang & Lau, 2019), service quality attributes (Ju, Back, Choi & Lee, 2019), brand personality (Lee & Kim, 2018), consumer experience (Pappas, 2019), consumer segmentation (Lutz & Newlands, 2018), distrust (Sthapit & Björk, 2019b), motivations and constraints (So, Oh & Min, 2018), perceived value (Mao & Lyu, 2017; Zhu, So & Hudson, 2017), social benefits (Tussyadiah, 2016), behavioural intention (Lalicic & Weismayer, 2017) and unique experience (Mao & Lyu, 2017). Despite the dominance of online platforms as the primary facilitators of exchange in the sharing economy (Pappas, 2019; Tussyadiah & Pesonen, 2016), few studies have examined users’ perception of and satisfaction in using the Airbnb website (Wang & Jeong, 2018), including the determinants of users’ continuance intention (Sthapit & Jiménez-Barreto, 2018b).

This study seeks to address this research gap beginning with a discussion of the related theoretical arguments and concepts. First, value is an implicit criterion for making decisions and evaluative judgments (Holbrook, 1996). Evidence has suggested that a multidimensional conceptualisation of customers’ values can predict customers’ satisfaction more reliably than a one-dimensional approach can (Leroi-Werelds, Streukens, Brady, & Swinnen, 2014). Consumers who participate in creating value in the consumption process have been found to be more satisfied than passive agents (Navarro, Linares, & Garzon, 2016).

Second, co-creation is a consumer experience of a particular kind; specifically, it is a participatory and interactive experience (Prahalad & Ramaswamy, 2004). Today, tourists are considered co-creators of their own experience (Prebensen, Vittersø, & Dahl, 2013), with co-creation positively affecting their satisfaction with vacation experiences (Mathis, Kim, Uysal, Sirgy, & Prebensen, 2016). Establishing a pre-exchange dialogue with tourists is a prerequisite to the co-creation of experiences because it helps tourism service providers understand tourists’ needs and expectations (Chathoth, Ungson, Harrington, Altinay, Okumus, & Chan, 2014).

Third, in the pre-trip planning process, tourists are receptive to acquiring new information to obtain more attractive alternatives (Decrop & Snelders, 2005). However, tourists still face uncertainties related to unanticipated events (Hyde & Decrop, 2011) due to, for example, the overabundance of information (Eppler & Mengis, 2004). This phenomenon is typically called ‘information overload’. This issue can lead to post-decision regret (Inbar, Botti, & Hanko, 2011) and dissatisfaction (Tsiros & Mittal, 2000).

Fourth, studies have recognised that providing customers with services that lead to their satisfaction has the most significant effect on continuance intention (Akter, D’Ambra, & Ray, 2013; Lee, 2010). Consumer satisfaction is also a source of competitive advantage in the lodging industry (Halstead & Page, 1992; Pizam & Ellis, 1999).

This study aims to examine the simultaneous effect of the dimensions of consumption values (functional, social and emotional), co-creation and information overload on satisfaction in relation to accommodation booking using the Airbnb website, together with how this effect impacts the continuance intention of Airbnb’s customers. In other words, this study focuses on the development of a new model that assesses tourists’ satisfaction with the pre-trip accommodation booking experience and their continuance intention with regard to adopting
emerging sharing-economy platforms like the Airbnb website, based on the dimensions of consumption values (functional, social and emotional), co-creation, information overload, satisfaction, and continuance intention.

Specifically, this study deepens the current body of knowledge in several ways. First, it provides insights into Airbnb consumers’ satisfaction in making website bookings. Second, it enriches the theoretical and empirical perspectives of continuance intention in the context of the sharing economy. Third, its findings will help both Airbnb’s website developers and its hosts facilitate a booking experience that augments consumers’ satisfaction and continuance intention.

2 Theoretical framework and hypothesis development

The theoretical framework used in this study provides the definitions of satisfaction and its antecedents, namely, consumption values (conceptualised as a multidimensional construct of functional, social, and emotional values), co-creation, information overload, and outcome, that is, continuance intention, as well as their interconnections (Figure 1). This section also provides the definitions of sharing and the sharing economy as well as their distinction.

2.1 Sharing, the sharing economy and their distinction

According to Quinn and Powers (2016), the concept of sharing is routinised and rarely draws attention, unlike gift-giving practices. Sharing is constitutive of social relations and consists of two dimensions: communion and distribution. The communion dimension includes the exchanging a story or an emotion as a gesture of openness or mutuality, which enhances intimacy. The distributive dimension refers to the distribution or division of a resource among those with common economic interests, including dividing up a whole (e.g. a pie or a room) with each individual able to lay claim to a portion, for example, sharing of material objects, emotions or information (John, 2013). In addition, sharing by definition does not include financial remuneration (Belk, 2007). On the contrary, the sharing economy as an economic model enables individuals to share access to under-utilised goods or services for monetary or nonmonetary benefits (Belk, 2014; Ferrell, Ferrell, & Huggins, 2017). In other words, the sharing economy is an economic system in which an online platform connects the supply and demand sides to facilitate transactions of giving temporary access to idle resources (Gonzalez-Padron, 2017). On the supply side, Airbnb, a sharing economy platform, enable rental hosts to list their available accommodation on Airbnb and profit by renting it out, usually at cheaper rates than comparable hotels (Varma, Jukic, Pestek, Shultz, & Nestorov, 2016). On the demand side, Airbnb fulfils travellers’ needs, such as accommodation with lower prices (Guttentag, 2015; So et al., 2018), leading to savings (Varma et al., 2016). In addition, the price attribute is central to the notion of sharing economy (Guttentag et al., 2018).

2.2 Satisfaction

Satisfaction is a sense of contentment that arises from an actual experience in relation to an expected experience (Hernon & Whitman, 2001). More narrowly, Bhattacherjee (2001) defined it as an individual’s emotional or psychological state following virtual community usage experiences, e.g., those with software, platforms, new technology devices (Liang, Choi, & Joppe, 2018), or, in the context of the current study, the Airbnb website. Some researchers have conceptualised satisfaction as an emotional reaction extracted from consumption...
experiences (Huang, Weiler, & Assaker, 2015). In the tourism context, satisfaction is defined as the outcome of the difference between the expectation and the actual experience (Chen & Chen, 2010). Specifically, a tourist is considered satisfied if a feeling of pleasure—a positive, memorable feeling—results from a comparison of his or her expectations and experiences upon leaving a destination (Su, Cheng, & Huang, 2011).

Satisfaction is an antecedent of continuance intention (Akter et al., 2013; Deng, Lu, Wei, & Zhang, 2010; Gallarza, Saura & Moreno, 2013; Leri & Theodoridis, 2018; Zhou, 2011). Deng et al. (2010) examined Chinese consumers’ continuance intention with regard to mobile instant messaging and showed that satisfaction has a positive influence on loyalty. Zhou (2011) found that users’ post-adoption behaviour in relation to mobile services is strongly determined by their level of satisfaction. This leads to the hypotheses that follow.

2.2 Antecedents associated with satisfaction
2.2.1 Theory of consumption values

The theory of consumption values, which was developed by Sheth, Newman and Gross (1991), focuses on the consumption values that explain ‘why consumers choose to buy or not to buy (or use or not use) a specific product, why consumers choose one product type over another’ (p. 159). This theory can be applied to different product categories, e.g. durable and nondurable consumer goods, industrial goods and services (Williams & Soutar, 2009).

According to Sheth et al. (1991), the theory of consumption values has at its base three fundamental axiomatic propositions: the consumer’s behaviour is a function of various consumption values, the consumption values make different contributions in any purchase situation, and the consumption values are independent. Therefore, any or all of the five consumption values can influence a decision. Each of these values plays a different role in specific buying situations, each relates additively, and each contributes incrementally.

Chen and Chen (2010) suggest that the validity of a unidimensional measure of consumption value is open to criticism due to its assumption that consumers have a shared meaning of value, while a multidimensional scale can overcome the validity problem by operationalising perceived value using, for example, a five-dimensional construct consisting of social, emotional, functional, epistemic, and conditional responses (Sheth et al., 1991). Sheth et al. (1991) argued that the five values are critical in influencing consumer decision choices. However, the theory of consumption values also argues that the relative importance of the value components likely varies from context to context (Sheth et al., 1991; Sweeney & Soutar, 2001; Teng, 2018). Moreover, many existing tourism studies adopt a wider view that treats the concept of perceived value as a multidimensional construct (Bajs, 2015; Paraskevaidis & Andriotis, 2015; Prebensen & Xie, 2017; Sabiote-Ortiz, Frías-Jamilena, & Castañeda-García, 2016; Sweeney & Soutar, 2001). Based on their analysis of these works, the researcher identified four common dimensions of perceived value: functional value, emotional value, social value, and monetary value. In the same vein, Similarly, Sweeney and Soutar (2001) developed the Consumer Perceived Value (PERVAL) scale for measuring consumption values, including emotional value, social value, quality/performance, price/value for money and eliminating the epistemic and conditional dimensions. Petrick (2002) posits a scale consisting of five components: behavioral price, monetary price, emotional response, quality, and reputation. In addition, to measure the onsite perceived value, Prebensen, Woo, Chen, and Uysal (2013) suggest four distinct dimensions: emotional, social, quality, and price.

The current study uses only three dimensions—functional, social, and emotional—to measure the construct of consumption values. Sheth et al. (1991) defined functional value as the ‘perceived utility acquired from an alternative’s capacity for functional, utilitarian, or physical performance’ (p. 72). This dimension might include, for example, dependability,
endurance, and price. Next, social value refers to the perceived utility resulting from a product or service’s association with one or more social groups, e.g., demographic, socioeconomic, and cultural groups. Last, emotional value designates the gain acquired from customers’ feelings or affective states after consuming products and services (Sheth et al., 1991). Many studies have confirmed the positive influence on satisfaction of perceived value derived from a service experience (Kesari & Atulkar, 2016). In the same vein, tourism studies disclose that the perceived value dimensions affect satisfaction positively (Gallarza & Saura, 2006; Mohd-Any, Winklhofer, & Ennew, 2015; Prebensen, Woo, & Uysal, 2014; Williams & Soutar, 2009). Accordingly, we present the following hypothesis.

H1: Consumption values (H1.1: functional value; H1.2: social value; H1.3: emotional value) directly and positively affect satisfaction in using the Airbnb website for accommodation booking.

2.2.2 Co-creation

Prahalad and Ramaswamy (2004) were among the pioneering scholars who developed the concept of co-creation as the next level of value creation practices. By introducing the service-dominant (S-D) logic with a set of foundational premises, Vargo and Lusch (2004) advanced the service research field by suggesting that the customer is not a passive recipient of pre-existing value but is always an active creator of value. S-D logic views co-creation in terms of participatory, interactive activities that involve different actors, while value is defined as ‘value-in-use’, i.e., ‘the value for customers, created by them during their usage of resources’ (Grönroos & Gummerus, 2014, p. 209). In other words, S-D logic suggests that customers must play an active part together with the firm in co-creating experiences and value (Chathoth, Ungson, Harrington, & Chan, 2016; Heo, 2016; Oyner & Korelina, 2016; Vargo et al., 2008; Vargo & Lusch, 2004).

Minkiewicz, Evans, and Bridson (2014) defined co-creation as the experience that is created by the customer through active participation in activities, engagement, and personalization of the experience. Grönroos (2012) modelled co-creation in service as a platform on which value co-creation occurs in direct interactions between customers and service providers. Despite the differing perspectives on value co-creation, all the categorizations share a common concept: direct interaction between providers and customers (Zhang, Jahromi, & Kizildag, 2018), and studies affirm that interaction is an important dimension of co-creation (Etgar, 2008; Prahalad & Ramaswamy, 2004; Yi & Gong, 2012). In addition, co-creation provides collaboration opportunities between firms and consumers so that both (a) benefit from the activity, (b) willingly participate in the activity, and (c) acknowledge their own and the other party’s role as contributors to the development of customer practices and processes (Payne, Storbacka, & Frow, 2008).

Studies indicate that in the Airbnb context, tourists increasingly seek to collaborate by co-creating their own experiences with the host, resulting in meaningful value formation (Neuhofer, Buhalis, & Ladkin, 2012; Smaliukiene, Chi-Shiun, & Sizovaite, 2015). Further, empirical evidence is increasing for the relationship between participation in value creation and satisfaction. Customers are active participants in the value co-creation process (Vargo & Lusch, 2008) and interact with the company to enhance satisfaction (Grönroos, 2008). For example, Navarro et al. (2016) studied spa services and found a positive relationship between co-creation and customer satisfaction, and Grissemann and Stokburger-Sauer (2012) suggested that tourists who participate in co-creation processes become more satisfied than those who do not. On these theoretical grounds, we propose the following hypothesis.
H2: Co-creation directly and positively affects satisfaction with using the Airbnb website during accommodation booking.

2.2.3 Information overload

Feather (1998) described information overload as the point where the abundance of information prevents the effective use of the information. Information overload simultaneously considers the number of alternatives and the attributes of those alternatives (Scheibehenne, Todd, & Greifeneder, 2010) but places greater emphasis on the attributes of the alternatives (Park & Jang, 2013). The performance (i.e. the quality of decisions or reasoning in general) of an individual correlates positively with the amount of information that he or she receives, up to a certain point. If further information is provided beyond this point, then the performance of the individual will rapidly decline (Chewning & Harrell, 1990). For example, such information overload may occur in a grocery store context before a display of a large array of possible selections, e.g. a wide variety of wine choices. In this case, the consumer can rapidly become frustrated and perhaps make a suboptimal choice (Jacoby, Speller, & Kohn, 1974).

In an online service setting like Airbnb, potential information overload can result from the virtually unlimited quantity of information a consumer can find and the largely unknown source and quality of information (Gottschalk & Mafael, 2017; Hu & Krishen, 2019). Studies indicate that the vast amount of information in online communities is not always helpful (Park & Lee, 2009; Zhu & Zhang, 2010), and a tremendous amount of product/service information often complicates consumers’ decision-making processes (Pan & Chiou, 2011). Faced with huge amounts of online information, consumers place a premium on information quality, and a lack of quality information will influence the consumers’ service experience online (Ghasemaghaei & Hassanein, 2016). According to Martin-Fuentes, Fernandez, Mateu, and Marine-Roiga (2018), simplified integrative classification systems, easily understood by all, such as accommodation star-rating levels or simplified indicators, could help Airbnb users overcome information overload. Moreover, Airbnb uses a quality certification called ‘Superhost’ that serves to prevent information overload. However, the percentage of properties that have the ‘Superhost’ badge on Airbnb is very limited (Liang, Schuckert, Law, & Chen, 2017).

Studies have indicated that having too much information to process may reduce consumer satisfaction (Malhotra, 1982; Keller & Staelin, 1987). Indeed, too much choice information makes selection among these alternatives difficult because working through alternatives to remove some while keeping others of interest strains the use of cognitive resources (Sweller, 2010). Such a cognitive load taxes the resources in working memory that are needed to process the incoming information, thus leading to poorer decisions and more negative responses (Ko, Seo, & Jung, 2015). People experiencing overload are less likely to be satisfied with their decisions (Botti & Iyengar, 2004; Tsiros & Mittal, 2000). This leads to the following hypothesis.

H3: Information overload has a negative effect on satisfaction with using the Airbnb website during accommodation booking.

2.3 Outcome associated with satisfaction
2.3.1 Continuance intention

Continuance intention is the strength of consumers’ intention to perform a specified behaviour (Bhattacherjee, 2001). It is also congruent with repeat purchase decisions (Kang, Hong, & Lee, 2009). Continuance intention refers to an individual’s judgment of whether to
repurchase a specified product or service from the same business, taking into account his or her current situation and likely circumstances (Hellier, Geursen, Carr, & Rickard, 2003). Continuance decisions are not made in a vacuum. For most services, there are alternatives that may influence users’ decision to continue their usage, depending on their satisfaction with that product or service. For example, individuals who have a positive experience with software or social networking sites tend to have a higher continuance intention compared to those who have a negative experience (Sibona, Cummings, & Scott, 2017). The concept of continuance intention has been discussed in the information systems literature (Bhattacherjee, 2001); however, it has rarely been studied in the context of tourism (Choi, Wang, & Sparks, 2019).

3 Methods

3.1 Pilot test, data collection, and data analysis tools

The authors pre-tested the questionnaire with four academic researchers possessing expertise in topics related to the present study as well as with 30 Italians who reported having experience using Airbnb to confirm the relevance, clarity, flow, and phrasing of the questions. The potential respondents were identified by relying on the personal network of one of the members of the research team. During the pilot test, none of the participants reported being annoyed by the length of the survey. According to them, the survey could be completed in around seven minutes.

The survey consisted of two parts. The first part asked the respondents whether they had booked accommodation using the Airbnb website in the last 12 months. Only those individuals who gave a positive answer to this question could participate in the study. After asking respondents to recollect their most recent Airbnb booking experience, the survey then asked questions about their socio-demographic profile (i.e. age, gender, education and occupation) and to answer some questions related to their experience with Airbnb (i.e., ‘When did you start using Airbnb?’ and ‘How many bookings have you made through Airbnb in the past year?’). The second section included multi-item scales that measured the following five constructs: consumption values (i.e., functional, social, and emotional), satisfaction, co-creation, information overload, and continuance intention. This study adopted its measurement items from previous studies with slight modifications. The study measured consumption values using 13 items adapted from Sweeney and Soutar (2001). Satisfaction included three items adapted from Udo, Bagchi, and Kirs (2010). Co-creation used three items adapted from Buonincontri, Morvillo, Okumus and van Niekerk (2017). The three scale items adapted from Chen, Shang, and Kao (2009) measured information overload. The three scale items measuring continuance intention were adapted from Bhattacherjee (2001). In total, the survey included 25 items. The participants responded to each item using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) (Table 1).

Table 1

Following numerous recent studies linked to Airbnb that employed a quantitative approach using an online survey (Guttentag et al., 2017; Jiang, Balaji & Jha, 2019; Ju et al., 2019; Lee & Kim, 2018; Mody et al., 2019; Lutz & Newlands, 2018; Wang & Jeong, 2018), the researchers for the current study adopted a quantitative approach using a self-administered online survey and convenience sampling. The subjects were generated from 1,000 contacts of an Italian tourism association based in Italy. These 1,000 individuals received an email inviting them to complete the online questionnaire by clicking on a link provided in the email. After a three-week survey period (during September 2018), the researchers received a total of 260 valid
questionnaires, of which the study used 259 for statistical analysis. One case was considered an outlier and was excluded from the analysis due to its high Mahalanobis d-squared value.

4 Results

4.1 Profile of the respondents

The respondents were mostly female (54.8%). The majority of survey participants (64.5%) were between 25 and 34 years of age. In terms of education, most had completed secondary school (51.4%) and 33.2% were self-employed. In response to the question, ‘When did you start using Airbnb?’, many responded ‘Four years ago’ (32%). The number of bookings made in the past year ranged from 1 to 20, with the highest for each person being 2 (38.2%).

4.2 Estimates of the model

To estimate the model, we implemented a confirmatory factor analysis (CFA) using the maximum likelihood module of AMOS 24. The CFA results showed a very good fit, as demonstrated by the goodness-of-fit diagnostics (Table 2). The CMIN/DF ($\chi^2$/df) was 1.483, which was below the threshold of 5 with 250 degrees of freedom, and the value of the confirmatory fit index (CFI) was very good (0.974, well above the threshold of 0.700 and greater than 0.950). Furthermore, the root mean square error of approximation (RMSEA) was 0.043 (with LO 90=0.034 and HI 90=0.052), which was lower than the critical and worldwide minimum limit of 0.08 (Hair, Black, Babin, & Anderson, 2014), with an expected cross-validation index (ECVI) as high as 2.018. The fit of the model was very good, as $\chi^2$/df was below 3, the CFI was above 0.95 and the RMSEA had a value of 0.043, which was significantly below the critical value of 0.08. The goodness-of-fit index (GFI), normed fit index (NFI), relative fit index (RFI), incremental fit index (IFI), Tucker–Lewis index (TLI) and parsimonious NFI (PNFI) values were 0.899, 0.924, 0.909, 0.974, 0.968, and 0.770, respectively. Being above 0.8 and 0.9, respectively, the values of GFI and NFI were very good.

The above estimation of the model based on the seven constructs was very good. According to Kenny (2005), the model fit is very good when N>200 (in our case, N = 259), Hoelter’s critical N statistic is greater than 75 and the chi-square is statistically significant (Hoelter = 201 at the 0.05 significance level and/or Hoelter = 213 at the 0.01 significance level; Table 2). Therefore, the value of CFI (0.974 in our case) was not the only measurement that could be used to determine whether the model fit was very good or satisfactory. In our case, the model fit was very good. Furthermore, the value of the parsimonious comparative-of-fit index (PCFI) was 0.811, which, being greater than 0.750, satisfied one of the two assumptions of a well-fitting parsimonious model (Rigdon, 1996). Furthermore, the second assumption of Rigdon (1996) was satisfied as well, as the CFI value was above 0.95.

We followed Hair et al. (2014) and initially unidimensionalised (i.e., constrained) the largest estimated variable of each construct. Next, we correlated the errors of the variables for their modification indices (MI) in the findings that had high covariance (greater than MI = 11.000; i.e., e11 to e12 = 22.995, e7 to e8 = 11.563, e12 to e13 = 24.264, and e11 to e13 = 15.318). The parentheses in Table 2 show that the model fit estimates were very good without correlating the errors of the variables that had high covariance. While checking the observation farthest from the centroid (i.e., the Mahalanobis distance), we found that observation or case number 156 had a high Mahalanobis d-squared value of 86.021. In addition, some of the variable values of the 156th case were above the means of the variables, i.e., X8, X11, X12, X13, X16, and X19, and some were below of the means of the variables, i.e., X3, X4, X5, X9, X15, X20, and X23. Consequently, we deducted this case from the sample and reduced the
total sample size used in the analysis from the initial 260 cases to 259. The removal of this case resulted in the further improvement of the estimates of the model and the reliability and validity of the findings. Finally, there was no need to extract variables from the model, as there remained no standardised regression weights with values less than 0.5.

As Table 2 shows, the goodness-of-fit diagnostics in the CFA results suggested a very good fit.

Table 2

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Table 3 shows the correlation matrix of the seven constructs. No multi-collinearity problems existed, as the correlations were below 0.7.

Table 3

Based on Hair et al. (2014), at the initial stages of the study, we checked the face validity, which is the most important validity test of the model and its constructs. Each construct should be meaningful and be based on previous existing scales. Face validity must be established prior to any theoretical testing when using CFA (Hair et al. 2014, p. 620). Based on Table 3, we calculated the square roots of the average variance extracted (AVE) and found that they were larger than the correlations between each construct and all other constructs. The construct reliabilities and the AVE for all seven constructs were calculated using CFA. All seven constructs of the model had reliabilities above 0.7 (functional value = 0.869, social value = 0.926, emotional value = 0.834, co-creation = 0.868, information overload = 0.869, satisfaction = 0.908 and continuance intention = 0.798). The average construct reliability was a very high 0.867.

The estimation of the Cronbach’s α of the constructs revealed high reliabilities (functional value = 0.865, social value = 0.938, emotional value = 0.875, co-creation = 0.866, information overload = 0.905, satisfaction = 0.865 and continuance intention = 0.763). These estimates suggested a satisfactory degree of reliability, as the mean construct reliability estimate based on Cronbach’s α was 0.868, which was well above the critical value of 0.7.

To assess convergent validity, we performed the following two steps. First, the loading estimates (i.e., the standardised regression weights of all 25 variables) were well above 0.5, (within the range of 0.531 to 0.949), showing satisfactory convergent validity. Given that 88% of the values of the loadings were above 0.7, we concluded that there was convergent validity. Second, the calculation of the AVE from each construct exceeded 50%, and thus, the model showed convergent validity. Specifically, the AVE for the seven constructs was above 50% (functional value = 0.626, social value = 0.758, emotional value = 0.504, co-creation = 0.687, information overload = 0.688, satisfaction = 0.767, and continuance intention = 0.578), and the AVE of all constructs was 0.658. Since each construct had an AVE>0.5, and as the AVE of all constructs = 0.658>0.5, the discriminant validity criterion of AVE>0.5 introduced by Fornell and Larcker (1981) was satisfied.

Fornell and Larcker’s (1981) criterion indicates that discriminant validity is established if the following proven condition holds: \( \text{AVE}_{i} > \max r^2_{ij} \forall i \neq j \) (Henseler, Ringle, & Sarstedt, 2015, p. 117). Therefore, this test verified the discriminant validity and the reliability of the analyses.

We tested the hypothesised associations between the constructs by estimating the structural equation modelling (SEM) fit using the maximum likelihood technique. The results showed that the NFI, CFI, RFI, IFI, and TLI had high values, as expected. The estimations of the various statistics show that the model had a very good fit with the data (Table 4). In addition, Table 4 reveals that five out of the six hypotheses were supported. The hypothesis that was not supported was that regarding the relationship between social value and satisfaction. According to the SEM analysis, we present the standardised path coefficients of the latent variables and
their standard errors, critical ratio (CR), and p-values in Table 4. The standardised path coefficients, particularly for the following four relationships, were positive and statistically significant at the 99% confidence level: functional value and satisfaction, emotional value and satisfaction, co-creation and satisfaction, and satisfaction and continuance intention. The standardised path coefficient for one relationship (information overload and satisfaction) was negative but significant at the 99% confidence level. Meanwhile, the standardised path coefficient for the remaining relationship (social value and satisfaction) was not statistically significant.

Table 4

5 Conclusion

First, this study contributes to the existing literature on the sharing economy by providing a new model for assessing tourists’ satisfaction with the pre-trip accommodation booking experience and their continuance intention for adopting sharing economy platforms, like Airbnb website. Previous studies have not examined both aspects simultaneously, making this study more holistic. In addition, by integrating the key constructs of consumption values, co-creation, information overload, satisfaction, and continuance intention into the model, this study extends the understanding of the antecedents and outcomes of satisfaction.

Second, an important finding of this research is that some values may be more influential in an Airbnb booking context. This finding supports some studies indicating that the relative importance of the value components likely varies from context to context (Sheth et al., 1991; Sweeney & Soutar, 2001; Teng, 2018). Specifically, functional value (H1.1) and emotional value (H1.3) are strong predictors of satisfaction in using the Airbnb website for accommodation booking. In addition, the study indicates that functional value is one of the main causes of consumers’ satisfaction in using the Airbnb website for accommodation booking because of the lower prices of different accommodations listed. This finding supports studies indicating price (functional value) as one of the main motives driving people to book Airbnb accommodations (Guttentag, 2015, 2016; Mao & Lyu, 2017; So et al., 2018; Sthapit & Jiménez-Barreto, 2018a; Tussyadiah & Pesonen, 2018) and affecting Airbnb consumers’ satisfaction (Hamari, Sjöklint, & Ukkonen, 2016) in the sense that Airbnb is used as an economical accommodation alternative (Zervas, Proserpio & Byers, 2014). For example, Tussyadiah and Pesonen’s (2018) study indicates the significance of the cost saving features as a factor driving consumers’ use of P2P accommodation. In the same vein, one of the commonly established dimensions of the Airbnb experience is cheaper price (Guttentag & Smith, 2017; Young, Corsun, & Xie, 2017). Moreover, the current findings indicate that if consumers experience enjoyment, relaxation, and pleasure during the pre-trip booking of their accommodations, they are more likely to be satisfied with such experiences. This finding supports some studies indicating that the emotional value or the affective state is of particular interest in experiential settings and significantly affects satisfaction evaluations (Otto & Ritchie, 1996; Williams & Soutar, 2009). However, the current study found that social value (H1.2) does not have an impact on satisfaction using the Airbnb website for accommodation booking. In other words, Airbnb’s association with demographic, socioeconomic and cultural groups does not have an impact on its customers’ satisfaction.

Third, the research supports the relationship between co-creation and satisfaction. Given that the Airbnb website is a crucial platform for users to search for information and complete transactions (Guttentag, 2015), a greater degree of communication between potential guests and hosts on the Airbnb website during accommodation booking in the pre-trip planning stage should be associated with higher satisfaction. This increased communication provides an opportunity for hosts to understand potential guests’ needs and expectations (Chathoth et al.,
2014), including likes or dislikes, preferences, and commonalities, thereby possibly further contributing to customer satisfaction. Furthermore, these findings seem to support the idea that using Airbnb to book accommodation serves as a way for travellers to interact with locals as cultural brokers (e.g., Smith, 2001), allowing them to familiarise themselves with the local identity and culture not only during their stay, as widely acknowledged by existing studies (e.g., Guttentag, 2015), but also during the trip planning process. Hence, we conclude that joint interaction is important in directly influencing customers’ satisfaction. Our results also support previous works that have indicated that co-creation positively affects customer satisfaction (Grissemann & Stokburger-Sauer, 2012; Grönroos, 2008; Navarro et al., 2016; Wang & Jeong, 2018).

Fourth, the findings support the hypothesised negative relationship between information overload and satisfaction (H3). In other words, a low degree of information overload during accommodation booking in the pre-trip planning stage is associated with higher satisfaction, thus providing evidence that the negative effects of information/choice overload (Keller & Staelin, 1987; Malhotra, 1982) occur not only in tourism and hospitality settings but also in the online domain. This contributes to addressing the recent call for further research on the effect of information/choice overload in the tourism and hospitality sectors (Sthapit, 2018c), given the lack of published papers examining the effect of information overload in relation to the Airbnb platform. Finally, this study also found a positive relationship between satisfaction in using the Airbnb website for accommodation booking and continuance intention.

Overall, the results indicate that satisfaction largely emerges through participation, lack of information overload, and the value created in and during the booking of accommodations on the Airbnb website. Customers will not feel more satisfied unless they actively participate in the booking, create a certain kind of value for themselves during the process, and are able to search for information and complete transactions without the need to process a large volume of information that exhausts their processing capacity.

This study offers both Airbnb’s website developers and its hosts several implications for facilitating a booking experience that augments consumers’ satisfaction and continuance intention. Given that functional value directly affects satisfaction in using the Airbnb website for accommodation booking, hosts should emphasise prices that are lower than those of hotels in the same location. There should be transparency in the prices of accommodations with no hidden costs. Hosts’ local knowledge may also help guests achieve economic value during their interactions in the booking stage. In addition, to help users experience enjoyment and pleasure during the booking process, hosts should include pictures of their facilities and information about nearby tourist attractions, restaurants and transportation. Hosts should clearly mention the facts related to the booking and disclose updated information about the accommodation’s condition on the Airbnb website, which may offer a relaxing and emotionally positive experience for consumers while using the site to book their accommodation. Hosts should actively interact with potential guests and answer questions about the booking and the quality of the accommodation to contribute to the guests’ satisfactory booking experience. The focus must be on building a positive relationship with potential Airbnb guests through active social interaction rather than merely providing cheap lodging. Meanwhile, Airbnb web developers should introduce more filters on the website to help customers acquire specific information without having to process an overabundance of information.

The present study has some limitations. The findings of this study are highly destination-specific, given that we collected the data only from Italian residents. The pilot testing of the questionnaire by relying only on the personal network of one of the members of the research team could have produced a possible bias. This study employed a convenience sampling technique; thus, the study findings could be misrepresented because of sampling selection bias. Moreover, the study was limited to the use of three dimensions of consumption values, co-
creation, information overload, and satisfaction to predict continuance intention. Furthermore, the present study adopted a web-based survey questionnaire. Adopting a greater array of research methods might overcome this limitation. The questionnaire was also developed in Italian, thus excluding non-Italian speakers.

Given the relatively small sample size of the current work, future research should consider examining a larger and more representative sample to offer more favourable empirical findings. In addition, since this study was conducted among Italian residents, upcoming studies could consider replicating our study across other countries or cultural backgrounds. Moreover, future research might elaborate on the model presented in this study by including other factors, e.g., choice overload (Sthapit et al., 2017), past experience, and self-efficacy (Wang & Jeong, 2018). Lastly, our study opted to investigate the extent to which functional value, social value and emotional value are individually able to influence satisfaction. Future research might consider testing a broader theoretical model where these three different values are recognised to compose a second order “consumption value” construct and then test this new model.

References


Figure 1 The conceptual model
**Table 1** Operationalization of constructs used in this study (variables sources and measurement items)

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Functional Value</th>
<th>Social Value</th>
<th>Emotional Value</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumption Values</td>
<td>X1 Airbnb is reasonably priced</td>
<td>X5 Using Airbnb helps me feel acceptable by others</td>
<td>X9 I enjoy using Airbnb service</td>
<td>Sweeney &amp; Soutar (2001)</td>
</tr>
<tr>
<td></td>
<td>X2 Airbnb offers value for money</td>
<td>X6 Using Airbnb service improves the way I am</td>
<td>X10 Airbnb make me wish to use it</td>
<td></td>
</tr>
<tr>
<td></td>
<td>X3 Airbnb is a good accommodation service for the price</td>
<td>perceived by others</td>
<td>X11 Making booking accommodation using Airbnb website lets me feel relaxed</td>
<td></td>
</tr>
<tr>
<td></td>
<td>X4 Using Airbnb is economical</td>
<td>X7 Using Airbnb makes a good impression on other people</td>
<td>X12 Using Airbnb makes me feel good</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>X13 Using Airbnb gives me pleasure</td>
<td></td>
</tr>
<tr>
<td>Satisfaction</td>
<td>X14 I am satisfied with my Airbnb booking experience</td>
<td>X15 Using Airbnb website is a pleasant experience</td>
<td>X16 Overall, I am satisfied with my Airbnb booking experience</td>
<td>Udo, Bagchi, &amp; Kirs (2010)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Co-creation (between Airbnb guest and host)</td>
<td>X17 I have directly interacted with my Airbnb host during the organization of my booking using Airbnb’s website</td>
<td>X18 While using Airbnb website for booking, I felt confident in my ability to collaborate/interact with my Airbnb host</td>
<td>Buonincontri, Morvillo, Okumus &amp; van Niekerk (2017)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>X19 I have been motivated by my host regarding the organization of my booking</td>
<td>X20 There are too much information on Airbnb website that I am burdened in handling it</td>
<td>X21 Because of too much information on Airbnb website, it is difficult to me to understand all of information</td>
<td>Chen, Shang, &amp; Kao (2009)</td>
</tr>
<tr>
<td></td>
<td>X22 I have no idea about where to find the information I needed on Airbnb website</td>
<td>X23 I intend to continue using Airbnb website for booking accommodation rather than discontinue its use</td>
<td>X24 My intentions are to continue using Airbnb website rather than using any alternative means when booking accommodations</td>
<td>Bhattacherjee (2001)</td>
</tr>
<tr>
<td></td>
<td>X25 I would like to continue my use of Airbnb website for booking accommodation.</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 2** Model fit summary*

<table>
<thead>
<tr>
<th>Model Fit Parameters</th>
<th>Estimates of Parameters of Default Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CMIN</td>
</tr>
<tr>
<td>CMIN</td>
<td></td>
</tr>
<tr>
<td></td>
<td>75(71)</td>
</tr>
<tr>
<td>GFI</td>
<td></td>
</tr>
<tr>
<td></td>
<td>.054(.059)</td>
</tr>
<tr>
<td>Baseline Comparisons</td>
<td>NFI, Delta1</td>
</tr>
<tr>
<td>Parsimony-Adjusted Measures</td>
<td>PRATIO</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>--------</td>
</tr>
<tr>
<td>RMSEA</td>
<td>.833 (.847)</td>
</tr>
<tr>
<td>ECVI</td>
<td>.043 (.073)</td>
</tr>
<tr>
<td>HOELTER</td>
<td>201 (125)</td>
</tr>
</tbody>
</table>

*Note: In parentheses we include the initial model fit estimates which are very good without correlating the errors of the variables that had high covariance (N=260). The estimates of parameters outside parentheses are based on N=259.

### Table 3: Correlation matrix and average variance extracted (AMOS 24, based on 259 cases) *

<table>
<thead>
<tr>
<th></th>
<th>F1</th>
<th>F2</th>
<th>F3</th>
<th>F4</th>
<th>F5</th>
<th>F6</th>
<th>F7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Functional Value</td>
<td>(.787)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social Value</td>
<td>.124</td>
<td>(.870)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Emotional Value</td>
<td>.632</td>
<td>.257</td>
<td>(.705)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Co-creation</td>
<td>.449</td>
<td>.194</td>
<td>.697</td>
<td>(.827)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information Overload</td>
<td>-.168</td>
<td>.324</td>
<td>-.206</td>
<td>-.292</td>
<td>(.829)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Satisfaction</td>
<td>.572</td>
<td>.089</td>
<td>.692</td>
<td>.660</td>
<td>-.261</td>
<td>(.875)</td>
<td></td>
</tr>
<tr>
<td>Continuance Intent</td>
<td>.567</td>
<td>.209</td>
<td>.669</td>
<td>.621</td>
<td>-.215</td>
<td>.660</td>
<td>(.745)</td>
</tr>
</tbody>
</table>

*Note: AVE in brackets () on the diagonal.

### Table 4: Test of hypotheses based on SEM*

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Hypothesised Relationship</th>
<th>Relationship</th>
<th>Estimate</th>
<th>SE</th>
<th>C.R.</th>
<th>p-values</th>
<th>Status of Hypotheses (at 99% confidence level)</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1.1</td>
<td>Functional Value to Satisfaction</td>
<td>F1 to F6</td>
<td>.315</td>
<td>.045</td>
<td>6.972</td>
<td>.000</td>
<td>Supported</td>
</tr>
<tr>
<td>H1.2</td>
<td>Social Value to Satisfaction</td>
<td>F2 to F6</td>
<td>.077</td>
<td>.059</td>
<td>1.301</td>
<td>.193</td>
<td>Non-supported</td>
</tr>
<tr>
<td>H1.3</td>
<td>Emotional Value to Satisfaction</td>
<td>F3 to F6</td>
<td>.629</td>
<td>.070</td>
<td>9.043</td>
<td>.000</td>
<td>Supported</td>
</tr>
<tr>
<td>H2</td>
<td>Co-creation to Satisfaction</td>
<td>F4 to F6</td>
<td>.530</td>
<td>.063</td>
<td>8.487</td>
<td>.000</td>
<td>Supported</td>
</tr>
<tr>
<td>H3</td>
<td>Information Overload to Satisfaction</td>
<td>F5 to F6</td>
<td>-.184</td>
<td>.051</td>
<td>-3.634</td>
<td>.000</td>
<td>Supported</td>
</tr>
<tr>
<td>H4</td>
<td>Satisfaction to Continuance Intention</td>
<td>F6 to F7**</td>
<td>.510</td>
<td>.062</td>
<td>8.260</td>
<td>.000</td>
<td>Supported</td>
</tr>
</tbody>
</table>

* The tests of hypotheses are based on the final dataset (259 cases) without missing data.

** Dependent Variable: F7.