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The impact of information disclosure on consumer purchase behavior on sharing economy platform Airbnb

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ABSTRACT

Via the empirical evidences from Airbnb from eight major cities in U.S., we examine the role of information disclosure in influencing consumers' purchase behavior on this sharing economy platform. We analyze information disclosure from four aspects – namely, what information (i.e., information content), from where (i.e., information source), in what format (information presentation format), and how much (the quantity of information). We find all three information sources – providers, platform, and peer consumers – influence consumer purchase behavior. Regarding information posted by providers, we find a concave relationship between room information (i.e. the number of photos and the length of description) and consumer purchase behavior. However, no significant relationship between providers' self-description (texts and photos) and consumer purchase behavior is found. Regarding information posted by platform, both the recommendation from platform and provider verification information positively influence consumer purchase behavior. For provider-consumer interactions information, the providers' high response rate and fast response speed enhance consumer purchase behavior. However, providing connections to providers' social media profiles negatively influences consumers' purchasing behavior. Regarding the information from peer consumers, we find although consumers' overall ratings positively affect consumer purchase behavior, such influence diminishes when the ratings exceed certain thresholds. Our study provides implications for platform owners to optimize information presentation layout directly through the platform design or indirectly through the guidance to the providers' information disclosure to facilitate consumers' information search and acquisition to reduce the perceived risk, enhance trust on providers and the platform, and thus enhance their purchase intention and behavior.

1. Introduction

Sharing economy, also known as collaborative consumption, is burgeoning and fast developing world-wide in the past decade. Instead of buying and owning products/service capacity, consumers seek to lease under-utilized resources from resource owners. Hence, sharing economy provides opportunities for suppliers to redefine and distribute their offerings (Matzler et al., 2015). Sharing economy reflects the novelty value driver that generates new solutions to existing problems with technology innovation (Visnjic et al., 2017) in ride-sharing platforms (e.g., Uber and Lyft), accommodation-sharing platforms (e.g., Airbnb), office space-sharing platforms (e.g., LiquidSpace), transportation tool sharing platforms (e.g., Zipcar), parking space sharing platforms (e.g., JustPark), and other formats such as StyleLend for designer clothing sharing (Benjaafar et al., 2019).

Due to the uniqueness of the product offerings, consumers' limited consumption experience, physical distance between providers and consumers, and concerns over lack of regulation, consumers have high perceived risks towards sharing economy, which negatively affect their purchase intention and behavior (Liang et al., 2018a). Having more information available can improve consumers' perceived quality of products and services and signal the fairness of the price, which in turn enhances consumers' perceived equality and utility of the transaction (De Pelsmacker and Janssens, 2007). Available information can also reduce consumers' perceived risk when purchasing online (Kim et al., 2008). Particularly, information is used for communication and

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interactions among stakeholders for building/maintaining the relationship and facilitating transactions (Ert et al., 2016).

Through the empirical evidences collected from Airbnb, our study examines the influence of information disclosure on consumer purchase intention and behavior under the accommodation sharing context. Referring to previous studies (e.g., Hao and Tan, 2019), in this study, we define information disclosure as the joint actions of platform, providers, or consumers to reveal the product, service, or provider information through the online platform.

Our study aims to examine the role of information disclosure in influencing consumer purchase behavior through a comprehensive framework from four dimensions, namely, which information source, what information, in what format, and what information quantities consumers value; and how platforms may utilize the findings to better enhance consumer purchase behavior. For the first dimension, from the information source aspect, we examine the information posted by providers (e.g., product and provider information), peer consumers (e.g., ratings), and sharing economy platform (e.g., provider-consumer interaction, platform recommendation for accommodation, and provider verification). Thus, we raise our first research question: which information source(s) is (are) valued by consumers thus enhance(s) their purchase behavior in sharing economy?

For the second dimension, from the information contents aspect, we examine the information covering consumer's various decisions in sharing economy including product selection (referring to room information), provider selection (referring to provider information), and how these decisions are influenced by the platform information. Accordingly, we raise our second research question: what information is valued by consumers and consequently enhances their purchase behavior in sharing economy?

For the third dimension, from the information format's perspective, we examine the role of information formats in enhancing consumer purchase behavior. The various formats include text description (e.g., room and provider description), visual description (e.g., room and provider photos), and quantitative description (e.g., peer consumer rating and price) etc. Correspondingly, our third research question is: in what presentation format (i.e., text, visual, or quantitative description) does the information is valued by consumers in enhancing their purchase behavior in sharing economy?

For the fourth dimension, from the information quantity's perspective, we examine the influence of the amount of information in consumer purchase behavior. Information is generally viewed as a resource benefiting consumers in terms of enhancing perceived value and reducing perceived risks of products and services (Xu et al., 2017a). However, in this always true? Thus, we raise our fourth research question as whether more information disclosed is always better in terms of generating consumers' purchase behavior in sharing economy.

In summary, the findings of this study suggest that all three information sources from providers, platform, and peer consumers affect consumer purchase behavior in sharing economy. First, regarding the information posted by the providers, our study suggests that providers' self-presented information such as the number of photos and the length of room description positively influences consumer purchase behavior. However, such influence diminishes with additional photos and text description, and thus the concave relationship is observed between products (i.e., rooms) information offering and consumer purchase behavior. In addition, our findings suggest that providers' self-description, in terms of texts and photos, does not affect consumer purchase behavior. Second, regarding the information posted by the platform, the findings of this study suggest that recommendations from the platform and provider verification information posted by the platform positively affect consumer purchase behavior. In addition, in terms of the provider-consumer interactions information posted by the platform, the findings suggest that both the providers' high response rate and fast response speed enhance consumer purchase behavior. However, providers' social media profile connections negatively influence consumers' purchasing behavior. Third, regarding the information from peer consumers, our findings suggest that although consumers' overall ratings positively affect consumer purchase behavior, such impact diminishes when the ratings exceed certain thresholds.

The findings of our study provide managerial implications for both providers and platform owners. For the providers, our findings can help them optimize their information disclosure strategy through posting specific information about products, services, and themselves with certain formats (e.g, text, photo, and video). For the platform owners, our findings may help them better understand their multi-roles in the sharing economy. Serving as an intermediary, platforms can use the findings of this research for better webpage design through the optimal information disclosure valued by consumers. Also being the facilitator of the peer to peer transactions, platforms can use the findings of this research to better regulate the providers and transactions, and to require or incentivize the providers to post specific information, prohibit certain information, verify their social identity, and disclose the verifications to consumers. By doing so, the platform may cultivate consumer trust toward both the platform and the providers, and thus enhance their purchase behavior. Our findings also suggest that platforms post certain information from the third-party perspective and encourage the interaction between providers and consumers.

Our study contributes to the previous studies about the impact of information disclosure on consumer purchase behavior from two main aspects. First, previous studies have examined the role of information in influencing consumer online purchase intention and behavior in general retail industries (e.g., Munzel, 2016; Tsai et al., 2011; Wells et al., 2011), but very few studies, if any, have focused on the role of information disclosure in sharing economy environment. In this study, we deal with the complexities of examining the role of information disclosure in the sharing economy context. Sharing economy is different from the pure online or offline contexts due to the platform role and interactions among various stakeholders. The platform not only serves as an intermediary to facilitate transactions, but also regulates the sellers, consumers, and their transactions (Akbar and Tracogna, 2018). The information can be posted by a variety of the above stakeholders, which can all affect consumer purchase behavior. The high variety and uniqueness of product and service offered in sharing economy lead to the necessity of various information disclosure strategies. For example, in addition to the previous discussion on the role of product and service description and consumer evaluation information on consumers' purchase behavior (e.g, Lin et al., 2019; Wang et al., 2019), our study shows that providers' social interactions with consumers (in terms of the providers' high response rate and fast response speed) enhance consumers' purchase behavior in sharing economy. In addition, the platform plays a significant role in disclosing the recommendation information and regulating the providers, which also has significant effects on consumers' purchase behavior in sharing economy.

Second, most of the previous studies have examined the optimal information disclosure strategy from one single aspect, such as contents (Ert et al., 2016) or information source (Zhang et al., 2010). In sharing economy, various information releasers such as providers and the platforms need to make multi-dimensional decisions including the contents, quantity, and format of the disclosed information to enhance consumers' familiarity with the offerings and their providers or platforms. In this way, our study investigates the information disclosure through a comprehensive framework including four dimensions, namely, which information source, what information, in what format, and what information quantity to disclose. Although previous studies (e.g., Li et al., 2019; Wang et al., 2016) emphasizes the positive effect of information disclosure in consumers' purchase behavior, our findings suggest that such effect depends on the information source, contents, and format. In addition, we find the relationship between the quantity of the product information disclosed and consumer purchase behavior is concave. Namely, the positive marginal effect of information disclosure on consumers purchase behavior decreases with the larger amount of information.

The rest of the paper is organized as follows. Section two reviews the relevant literature. Section three introduces the theoretical foundation of this study and develops the hypotheses. Section four describes the data collection and variable measurements. Section five presents the results from the regression models and discusses the results. Section six discusses the theoretical and managerial implications. Section seven concludes this study and discusses the limitation and directions for future research.

2. Literature review

2.1. Sharing economy

Sharing economy, also known as collaborative consumption, is burgeoning and fast developing (Matzler et al., 2015). More people have become used to sharing and leasing products, instead of buying and owning them (Matzler et al., 2015). As a new business model, sharing economy firms are posing opportunities, but at the same time, challenged from various perspectives. On one hand, it is argued that sharing economy “empowers entrepreneurs” (Kane, 2016) and brings improved social welfare (Choi et al., 2019). On the other hand, sharing economy poses various social issues including lack of regulation, competing on an uneven ground with conventional corporate service providers, and potential exploitation of individual service providers (Cohen & Sundararajan, 2015; Kane, 2016; Matzler et al., 2015). Govindan et al. (2020) found lack of trust is the most influential barrier to achieve sustainable development goals of sharing economy.

Previous studies focusing on sharing economy can be categorized into three types. The first category (e.g., Chen and Hu, 2019; Hu, 2019) examined the supply and demand issues in the sharing economy two-sided market. The typical issues examined are the pricing (e.g., Gong et al., 2020; Wang et al., 2020) and supply-demand match strategies (e.g., Chen and Hu, 2019; Muren et al., 2019). For example, Chen and Hu (2019) examined the dynamical pricing and match strategies in the sharing economy. Muren et al. (2019) focused on the balance of demand and supply through investigating the maximum coverage location problem to reduce the imbalance of service level at various locations of the bike-sharing program. Hu (2019) discussed using dynamical pricing strategies to match supply with demand in the sharing economy industry. Wen and Siqin (2019) used mean-variance theory to find the optimal average quality levels and price that the platform should offer to the market. They also found product quality uncertainty and risk sensitivity have a significant influence on platforms’ optimal decisions and consumer surplus. Different from the above studies focusing on collaborative consumption among consumers, some studies found sharing economy can exist between enterprises such as between platform and sellers (Gong et al., 2020) and manufacturer and retailers (Li et al., 2020). For example, Gong et al. (2020) explored the online financing program through a sharing economy e-trailing platform perspective. Pricing is still one of the key decisions for the sellers to enhance their financial performance.

The second category of related studies (e.g., Zervas et al., 2017; Benjaafar et al., 2019) focused on the impact of the sharing economy on traditional business or the society. Previous studies examined the competitions between sharing economy and commercial market. For example, Zervas et al. (2017) examined the impact of Airbnb on hotel industry and found 1% increase in Airbnb listings results in 0.05% decrease of hotel quarterly revenues. Roma et al. (2019) analyzed the impact of Airbnb on the hotels’ pricing strategy and found budget and luxury hotels have different pricing response strategy to Airbnb. Benjaafar et al. (2019) found collaboration consumption can result in either high or low ownerships, and it can increase consumers’ surplus and enhance the social welfare. In addition, previous studies examined the corporation between sharing economy and traditional business. For example, Li et al. (2020) examined the cooperation between original equipment manufacturers and sharing economy platforms. They developed an analytical framework to discuss the mechanism that the original equipment manufacturers select business modes in the sharing economy. Further, studies (e.g., Asian et al., 2019) compared the supply chain management in traditional environment and sharing economy context. For instance, Asian et al. (2019) found sharing economy can generate additional profits to supply chain participants. According, they proposed a cooperative game model to fairly distribute these profits among the participants.

The third category of studies (e.g., Scholz, 2016; Liu and Mattila, 2017) examined consumers’ perception and behavior in sharing economy. The influential factors of consumers’ perception and behavior in sharing economy include the efforts and image of the platform and vendors on the platform. Liu and Mattila (2017) found the social image of sharing economy platforms and peer service providers plays an important role in consumer channel and provider selection because consumers value the feelings of belongingness and uniqueness offered by sharing economy. Yuan and Shen (2019) found the valuation of consumers determines their behaviors including purchase, rent, and product return. Scholz (2016) found the image, design, and transaction mechanism of the sharing economy platform influences consumer purchase behavior. Trust building process is important for consumers to make a purchasing/booking decision. Cheng (2016) found trust building becomes even more important under the new sharing economy environment when many encounters are at peer-to-peer and stranger-to-stranger level and decisions are made based on limited information available from internet. Yuan and Shen (2019) found price and costs influence consumers’ decisions in sharing economy.

Our study contributes to the third category as this paper also focuses on consumers’ purchase behavior in the sharing economy. Although previous studies (e.g., Scholz, 2016; Liu and Mattila, 2017) have discussed the influence of the efforts from the platform and vendors on enhancing consumers’ purchase behavior, very few studies examined how the information posted by the platform and vendors affects consumers’ purchase behavior. This study fills the literature gap through proposing a comprehensive framework of information measured by four dimensions and discussing their impact on consumers’ purchase behavior.

2.2. The influence of information disclosure on consumer purchase intention and behavior

Under the online shopping environment, consumers experience four transaction phases including information, agreement, fulfillment, and after-sales phases (Bauer et al., 2006). Among them, the information phase delivering the product and seller related information to consumers is listed as the most important phase to generate consumers’ purchase intention and behavior (Bauer et al., 2006). The information describes the functionality, accessibility, and enjoyment of the products (Li and Hitt, 2008). Such information may also indicate the qualification, credibility, and capability of the sellers (Xu et al., 2017b). Consumers are willing to pay a premium when more information about the seller is salient and accessible (Tsai et al., 2011).

Previous studies (Subramanian and Subramanyam, 2012; Xu et al., 2017a) have examined the influence of information disclosure on consumers’ purchase intention and behavior. Regarding the content of information, Xu et al. (2017a) investigated how the information of e-service offerings in each stage of online shopping processes may influence consumers’ purchase behavior, and how such influence depends on the product category – utilitarian or hedonic, and low or high perceived risks. Subramanian and Subramanyam (2012) showed that sellers’ reputation information, product condition, and warranty information influence consumers’ purchase behavior. Regarding the source of information, Munzel (2016) found releasing the source of information provider can positively affect consumer purchase intention and behavior. Zhang et al. (2010) compared the influence of two information sources in restaurant industry: consumers' comments and third-party booking website editors' recommendation. It is found that editors' recommendation has more significant influence than other consumers' comments. Regarding the quantity and quality of information, De Pelsmacker and Janssens (2007) found both the quantity and quality of information have a significant influence on consumers' purchase behavior directly or indirectly through affecting consumers' attitude toward products. Regarding the benefits and costs of information disclosure, Liu et al. (2017) found the more and accurate information available can push sellers to increase retail price, which shows the downsides of information availability for consumers. Regarding the motivation of information disclosure, Hao and Tan (2019) compared the different incentives of facilitating information disclosure from retailers and suppliers, and found these two parties can have opposing interests regarding more information disclosure.

Our study focuses on the benefits of information disclosure on consumers' purchase behavior, and bridges the above four categories of previous studies through measuring the information through a comprehensive four framework with four dimensions – the information source, content, format, and quantity. In addition, we examine the benefits of information disclosure, namely, how each of the dimension of information affects consumers' purchase behavior, and provide guidelines for managers to refer to enhance consumer purchase behavior and the business profits through posting the optimal information from the appropriate people with the right content, format, and quantity.

2.3. *Consumers' perception and behavior in accommodation sharing*

One common context of sharing economy where previous studies (e.g., Lutz and Newlands, 2018; Roma et al., 2019) focused on is accommodation sharing. Previous studies examining consumers' perception and behavior in accommodating sharing can be categorized into three types. The first type of studies examined the motivation for consumers' purchase intention and behavior in the accommodating sharing. Guttentag et al. (2018) summarized the five reasons including interaction, home benefits, novelty, sharing economy ethos, and local authenticity. Both practical and experiential attributes attract consumers to adopt accommodating sharing.

The second category of studies examined consumers' attitude and perception toward the products and services in accommodating sharing. The core attitude and perception include low familiarity and high perceived risks. Liang et al. (2018a) found consumers have low familiarities with the products and services offered by Airbnb because the products and services offered by sharing economy are less standardized with various forms, which results in little or no prior consumption experience for consumers. Sutherland and Jarrahi (2018) found consumers have high perceived risks toward accommodation sharing economy. This is because Airbnb is considered less regulated when compared with the traditional hotel industry in terms of the mandatory amenities, facilities, and operating standards (Wang and Jeong, 2018). In addition, providers who offer the products and services can have different backgrounds (Ert et al., 2016).

The third category of research investigates the influential factors of consumer purchase intention and behavior in accommodation sharing economy. The complex environment in Airbnb results in consumers' purchase intention and behavior being influenced by many factors (Tussyadiah and Park, 2018). Internally, consumers' positive perception can enhance their purchase intention and behavior. These positive perception examined in previous studies include trust (Liang et al., 2018b), attachment (Yang et al., 2019), self-brand connection, meaning the extent of perceived overlap between the brand and the consumer themselves, sense of power (Liu and Mattila, 2017), attitude toward the hosts and platform, subjective norm, perceived value (Mao and Lyu, 2017), price sensitivity (Liang et al., 2018a), and consumer personality (Poon and Huang, 2017) and characteristics (Lutz and Newlands, 2018). The negative factors include the perceived risk (Mao and Lyu, 2017). The external factors refer to the efforts and actions implemented by host or the Airbnb. The efforts from hosts discussed in previous studies include advertising (Liu and Mattila, 2017), posting hosts' personal photos (Ert et al., 2016), host-guest relationship management (Wang and Jeong, 2018), pricing (Gibbs et al., 2018), and the perceived quality of product and services (Priporas et al., 2017). The efforts from Airbnb platform researched in previous studies include the website design showing perceived usefulness and easiness of the website (Wang and Jeong, 2018), regulation and authenticity (Lalicic and Weismayer, 2017), and reputation of the Airbnb (Zervas et al., 2015).

Our study is categorized as the third type of the study focusing on examining the role of information disclosure by the hosts and Airbnb platform on consumers' purchase behavior. Only a few previous studies (e.g., Tussyadiah and Park, 2018) examined the influences of the efforts from the platform and hosts in posting information on consumers' perception and behavior in sharing economy. Among these few studies, most discussed the role of information from a single source such as provider photos (Ert et al., 2016) and descriptions (Tussyadiah and Park, 2018), without a comprehensive framework of information disclosure from various sources. This does not capture the various interactions among all stakeholders under sharing economy. Our study fills in this gap through examining the role of information posted in different contents, forms, and quantity from providers, peer consumers, and platform about products, providers, and regulations in influencing consumers' purchase behavior.

3. Theoretical background and hypotheses development

3.1. *Theoretical background*

The theoretical background of this study mainly lies on four theories: market signaling theory (Heil and Robertson, 1991), social exchange theory (Emerson, 1976), transaction cost theory (Hill, 1990), and information process theory (Gao et al., 2012). The commonalities of these four theories lie in the facts that they are all relevant to information, communication, and interactions between various parties, which are the cores of this study. Each of the theory also has certain unique insights from different perspectives.

Market signaling theory focuses on providers' perspective describing how providers post information as signals (i.e., extrinsic cues) to inform consumers about product and service quality, reduce uncertainties and misperception, and enhance consumer purchase intention and behavior (Wells et al., 2011). From the consumers' perspective, consumers differentiate the sources of the signals. Consumers may perceive the signals as being more reliable if they are difficult to fake, or supported by laws or social convention, or are costly to obtain or mimic (Donath, 2007), and may therefore trust such signals more (Flanagin and Metzger, 2013). In sharing economy, the information posted by the product or service providers (namely, the providers) and the platform are perceived as such signals by consumers. In our study, referring to the framework of signal and trust from previous studies (e.g., Rousseau et al., 1998), we focus on three categories of signals corresponding to consumers' each aspect of purchase decisions. The first category is the product signal reflecting product and service quality, which influences the consumers' product selection. The second category is the social signal reflecting provider's social identity, which influences consumers' provider selection. The third category is the institutional signals enabled by the sharing economy platform design and posted by the platform such as platform's recommendation and provider verification.

According to social exchange theory, consumers conduct the cost-benefit analysis to determine whether to build or maintain the relationship with the seller regarding economic exchange activities (Shiau and Luo, 2012). Sharing economy amplifies the complexity of this process from three aspects. First, the cost and benefit analysis becomes more complex due to various forms of costs and benefits. Regarding the cost, the monetary costs do not only include the room price, but also the service fee, cleaning fee, and occupancy taxes and fees. In addition to the monetary costs, the costs can have two additional forms in sharing economy. One is hassle cost in terms of the inconvenience and time cost associated with the booking process (Xu and Jackson, 2019), and the other is the perceived risk due to the concerns of security, social barrier of communication with providers and other consumers when sharing, and the economic lost (Sutherland and Jarrahi, 2018). Regarding the benefit, it can be from various sources not only limiting to the accommodation as room, amenities and facilities, but also from the psychosocial aspects such as fashion and hedonic feeling, social interactions with people, and ideological value of achieving sustainability (Geissinger et al., 2019). Second, the economic exchange either as monetary exchange or as social exchange happen between providers and consumers (Ritter and Schanz, 2019). Third, more stakeholders are involved in the sharing economy for consumers to build and maintain relationships such as between providers and consumers, between peer consumers, and between consumers and platform. Our study examines the influence of posted information on consumers' purchase behavior. The products and providers information offers important references for consumers to learn and enhance the familiarity, reduce perceived risk, and increase the perceived benefits. The institutional information refers to the recommendation and verification from the platform, which influences consumers' trust about the platform and providers as the antecedents of consumers' purchasing behavior in sharing economy (Netter et al., 2019).

However, does it always help increase consumers' purchase willingness by posting more information? In other words, do the consumers value all of the information posted? This is the core question which we aim to answer in this study. From the perspective of consumers, and according to transaction cost theory, more information posted will increase the asset specificity, indicating more uniqueness and rare features of the assets (Liang and Huang, 1998). This increases the transaction cost, particularly, the information search and acquisition cost for consumers, and reduces their purchase intention and behavior (Akbar and Tracogna, 2018). From the perspective of providers, too much information may not benefit them as well. This is because information disclosure needs providers' efforts and the associated costs, and not all information may be viewed as favorable or valuable from consumers (Liu et al., 2017). Some information may provide negative image in the eyes of consumers, which violates information provider's original intention of trying to increase positive appearance and improve consumers' familiarity toward them and their products. Instead, the additional information may cause consumer discomfort, displeasure, and infuriation (Hasan, 2016). Thus, there can be a tradeoff to post information online in sharing economy.

Lastly, according to the information process theory (Gao et al., 2012), the information processing capability of humans is limited. The span of information process for humans is only 5 and 9 chucks (as the memory units, Miller, 1956). Various information may have different perceived values. Consumers may differentiate the received information and deem certain information more valuable than others (Xu, 2020). Thus, consumers will filter the information and only focus on a narrow subset of information while ignoring other information (Turetken and Sharda, 2004).

In summary, information can both facilitate and prevent consumers' purchase behavior. This study examines what information is valued by consumers for their purchase behavior in sharing economy. We examine the role of information in influencing consumers' purchase behavior from six aspects regarding the information contents: product, provider identity, provider-consumer interaction, platform recommendation, provider verification, and consumer rating information.

3.2. Hypotheses development

3.2.1. The influence of product information on consumer purchase behavior

One of the significant disadvantages of online booking and shopping, compared with offline shopping, is the relatively high perceived risk caused by the distances between online sellers and buyers (Garbarino and Strahilevitz, 2004). Consumers can not feel and test the products before purchase, which raises consumers' perceived risk, especially for experiences related products (Dimoka et al., 2012). Posting product information through words description, pictures, videos, and other interactive tools conveys information about products and services quality, which improve consumers' quality perceptions (Wells et al., 2011) and provide economic reasons for purchase (Poppo et al., 2016). The product information enhances the perceived benefits and values from the cooperative transaction between seller and consumers, and enhances consumers' perceived utility (Wang and Hazen, 2016). In accommodation sharing context, the core products that consumers pay for is the use of the room and its amenities (Xie and Mao, 2017). According to previous studies (e.g., Xu et al., 2017a), product positioning influences the information disclosure by seller, and thus influences consumer purchase behavior. Regarding the core product in sharing economy – the room and the associated amenities, it has both the hedonic and utilitarian values because consumers stay in the accommodation in sharing economy can seek both fashion experiences and economic reasons. The rooms and amenities have higher perceived risks compared with traditional lodging rooms due to the large amount of varieties and unique and unfamiliar features of the rooms and amenities offered by various providers.

More product information available can also enhance consumers' cognitive perception: the rational expectations of the products and services, and thus enhance their purchase intention (Komiak and Benbasat, 2006). This enlarges the gap between consumers' perceived benefits and costs, which is the first step and the key for consumers to calculate the comparative value, and thus enhances consumers' purchase behavior (Hallikas et al., 2014).

Posting product information can also reduce information asymmetries and uncertainties (Wells et al., 2011). The product information in this study mainly refers to the text and visual descriptions about rooms and amenities. This is particularly beneficial under sharing economy environment, where the products and services are usually not standard, and have more varieties compared with conventional markets (Guttentag and Smith, 2017). Due to these reasons, consumers have less familiarity and higher perceived risk in sharing economy environment (Liu and Mattila, 2017). Having more information available can be particularly useful in sharing economy environment given that the high level of information asymmetry and economic risk exists (Ert et al., 2016). The product information can better enhance consumer familiarity toward the product and service, reveal the benefits, and reduce the potential risks and costs, which enhances consumer purchase intention and behavior (Wang and Hazen, 2016).

However, too much information may have downsides in generating consumers' purchase intention for several reasons. First, the large amount of information increases the search costs due to information overloading, and makes consumers harder to make comparisons with other products by being more time consuming (Gao et al., 2012). The rich information about product increases asset specificity, which increases transaction cost, and has a reverse relationship with consumer purchase behavior (Liang and Huang, 1998). Second, too much information can increase consumers' switching behavior to other sellers because not all detailed information is viewed as favorable from consumers' view (Liu et al., 2017). Third, the marginal benefit of information can decrease because consumers care more about the core, rather than auxiliary, attributes of products and service (Xu, 2020). Thus, extra information regarding auxiliary attributes is not valued as much as core attributes. Based on the above discussions, we hypothesize:

H1. There is a concave relationship between the amount of product (i.e., room) information and consumer purchase behavior.

3.2.2. The influence of providers' social identity information on consumer purchase behavior

The seller's social identity information in this study mainly refers to the text and visual description about providers. Posting sellers' social identity information can enhance consumers' familiarity of the demographic information about sellers, enhance the knowledge about the other party, and thus increase consumer purchase intention (Laroche et al., 1996). This is especially important in the peer-to-peer online sharing economy market (Ert et al., 2016).

Posting identity information about the sellers can also provide reputation and brand information about the sellers to consumers, which enhances their purchase intention (Fuller et al., 2007). The identity information can help consumers to better judge and evaluate the sellers, which influences their purchase intention (Xu et al., 2017b). The identity information of sellers all reveals the sellers' attributes, and enhances their attractiveness and trustworthiness, which both enhance their purchase intention (Ert et al., 2016).

In sharing economy, consumers are less familiar with the seller compared with in the conventional market due to the high varieties of seller identifications (Ert et al., 2016). The information of providers can be in the forms of text and photo descriptions, which are both self-presentation for providers aiming to make themselves socially visible encouraging consumers to potentially identify favorable appearance, high reputation, and qualified performance (Tussyadiah and Park, 2018). These all raise providers' trustworthiness because consumers raise their expectation and belief that the providers will act based on the descriptions that they convey through identity profile descriptions (Sutherland and Jarrahi, 2018). Consumers view the providers who provide self-identification visually through photos have more trustworthiness, and the potential effect of photos on consumers exceeds their mere presences (Ert et al., 2016). Therefore, consumers can have more evidence to judge the social attributes of the providers from these photos, which stimulates their feeling of the providers as reliable (Eckel and Petrie, 2011).

When the cheating cost, such as net costs of termination, is higher than cooperation, consumer purchase intention and behavior are raised (Parkhe, 1993). Posting social information can also increase the perceived cost of cheating and discourage opportunistic behavior (Poppo et al., 2016). Thus, the perceived net gain from the transaction is increased, which motivates consumers to make the transaction, and even cooperate and build relationship with the seller for longer terms to earn higher expected payoff (Parkhe, 1993). Posting identity information also improves seller's credibility and reduces perception of transaction risk (Ba and Pavlou, 2002). Thus, the consumer purchase intention and behavior are raised (Gefen et al., 2003).

Although provider identity information can help consumers learn more about the providers, it does not necessarily mean more information about provider identity is always better for several reasons. First, provider identity information is the self-disclosure information by providers, which may not be fully trusted by consumers (Walther, 2007). In addition, not every detail of the information about providers is favored by consumers (Tussyadiah and Park, 2018). Furthermore, consumers' perceived expertise and specialty of providers and the product and service that they offered may not be directly related to the self-presented information (Tussyadiah, 2016). Finally, consumers' information process capacity is limited, and too much information can cause information overloading, which leads to consumers' confusion and hesitation in making purchase decision (Gao et al., 2012). Too much information significantly increases the search cost, which reduces consumers' purchase intention (Akbar and Tracogna, 2018). Based on the preceding discussion, we advance the following hypothesis:

H2. There is a concave relationship between the amount of provider social identity information and consumer purchase behavior.

3.2.3. The influence of host-consumer interaction information on consumer purchase behavior

The provider-consumer interaction information in this study mainly refers to providers' responsiveness (i.e., response rate and time) to consumers' inquiries and the disclosure of their social network profiles (i.e., social network presence). Posting information about providers' responsiveness can increase consumers' sense of personal contact and motivate consumers to learn more about the product and transaction (Guttentag, 2015). This can enhance consumers' familiarity toward the providers and accommodation and reduce the perceived risk to generate purchase intention and behavior (Lutz and Newlands, 2018). Providers' high level of responsiveness expands the channel options consumers can communicate with the providers, which gives consumers the feeling as providers being approachable and trustworthy (Ert et al., 2016). The high response rate and fast response time also indicate the providers have the sense of willingness to interact with online community, be approachable, and have good communication skills and personalities (Tussyadiah and Pesonen, 2016). This facilitates the consumers to build and strengthen the connection with the providers and maintain a long-term relationship (Xie and Mao, 2017). Better interaction in terms of rapid and frequent responses and more reachable channels build the competitive advantage of the providers and indicate the providers are responsible (Ert et al., 2016).

Posting interaction information about the provider can enhance the trust between buyers and sellers, which strengthens the social relationship between them (Gefen and Straub, 2003). Social presence, as reflected by the information richness of social aspects, enhances consumer social based trust (Gefen and Straub, 2003). Social presence includes any information related to the social property of the people, such as the social interactions between people and their social network profiles. Social media activity presents the host's social life and provides additional information regarding the host's professional or personal network (Cheng and Jin, 2019). Such detailed information may enrich the social interaction between the host and consumers for consumers to better understand the hosts and enhance their familiarity toward them, which is an important antecedent of trust (von Hoffen et al., 2018). The social characteristics of trust are revealed by the psychological relationship between people. Efficient interaction between providers and consumers proves to be an effective approach to build social based trust (Carlson and Zmud, 1999). Based on the above discussion, we hypothesize:

H3. Posting provider-consumer interaction information including responsiveness (*H3a*) and social network presence (*H3b*) enhances consumer purchase behavior.

3.2.4. The influence of platform recommendation on consumer purchase behavior

Sharing economy designs and operates platforms to facilitate transactions among peers, and thus reflects the emerging and rapid development of platform economy. Platform economy refers to the economic activities that involve an online intermediary platform for independent sellers to sell unique services or products to consumers (Farrell and Greig, 2016). Thus, the design and role of the platform are influential to consumer purchase behavior.

Better design of websites serves as a signal enhancing consumer's products and services quality perceptions, reduces the information asymmetries and uncertainties, and thus enhances their purchase intention and behavior (Wells et al., 2011). The perceived effectiveness of e-commerce institutional mechanisms enhances consumer satisfaction on providers, which motivates consumers to place more trust in providers, and enhances their future purchase intention and behavior (Fang et al., 2014). The institutional information influences the perceived effectiveness of the online platform, which affects consumers' perceived risk and trust toward the platform. These influence their purchase intention and behavior from the platform (Pavlou and Gefen, 2004).

The design of the platform influences consumers' perceived usability of the platform, which can be defined as the perceived easiness of navigating and making transactions on the platform (Davis, 1989), and thus influences the purchase behavior (Flavián et al., 2006). In addition, the design of the platform influences consumers' perceived ethical performance of the platform, affects their subjective norm, and thus influences their purchase behavior (Yang et al., 2009). Different online platforms provide information of various quality, implement different delivery mechanisms, attract different sellers, have different features such as linguistic characteristics, sentiment, rating mechanism, perceived usefulness, and semantic features, which all influence consumer institutional trust and their purchase intention (Xiang et al., 2017).

In summary, for the website design, three factors are critical: technology, shopping, and product factors (Chen et al., 2010). Technology factors show the website design to facilitate the transaction, which can enhance the security, privacy, and usability of platforms (Ranganathan and Ganapathy, 2002). Sharing economy platform is a new technology for many consumers, and thus consumers have low familiarity and need to assess each step's use of the new system (Sutherland and Jarrahi, 2018). According to the technology acceptance model, the two key factors to influence consumers' attitude, intention, and actual adoption behavior under the internet and platform contexts are their perceived ease of use, as measured by the efforts that the consumers need to input, and the perceived usefulness, as measured by the benefits and value that the platform brings (Moon and Kim, 2001). The symbols in the purpose of recommendation posted by platform offer an efficient shortcut easier for consumers to navigate, and thus is helpful and convenient for consumers to obtain information (Xu, 2020).

The shopping factors show the website attributes that relate to the shopping experience. Consumers visiting the shopping websites mainly for two purposes. First, they want to search the products and compare, and thus how the information is delivered to enhance the shopping convenience is critical (Schaupp and Bélanger, 2005). Second, the process of navigating the website can bring hedonic values for consumers making them exciting and surprised (Bridges and Florsheim, 2008). Fashion and customized website design can help consumers to obtain more hedonic values during the website navigation (Thirumalai and Sinha, 2011). The symbols in the purpose of recommendation shows the platform's customized design and evaluation for each listing, which makes consumers have the interests in searching and comparing through those visualized symbols.

The product factors indicate the perceived quality of products or services, which can enhance the value and better reflect the features (Chen et al., 2010). The promotional symbols on room listing pages convey important demand information based on peer-consumers' purchasing behavior. Consumers generate trust through the information and recommendation from the platform as an intermediary because the evaluations from the third party is more subjective, and the information source has more credibility (Zhang et al., 2010). This raises the attractiveness of listings and also the consumers' expectation, which helps consumers generate more purchase intention and behavior (Xu, 2020). Thus, this study proposes the following hypothesis:

H4. Posting platform's recommendation information enhances consumer purchase behavior.

3.2.5. The influence of host verification on consumer purchase behavior

In sharing economy, in addition to serving as a transaction stage, the platform also serves the role of regulating, verifying, and supervising the online providers (Wang and Jeong, 2018). Thus, efficiently designed platform with institutional information about the mechanisms and details on how platform regulates, verifies, and supervises the online providers can enhance consumers' perceived credibility of the platform, provide ease of usage with resources on searching and selecting products and providers, perceive the evaluation of products and providers to be more objective, trust the platform, and reduce the information asymmetry (Wells et al., 2011). The verification of providers can also enhance consumers' perceived security and privacy during transactions and help consumers make final purchasing decision (Bauer et al., 2006). The verification of online providers may help with the challenge of lack of regulation in sharing economy by showing consumers that strict policies have been applied to online providers, and by motivating online providers to have self-regulation (Cohen & Sundararajan, 2015). This can also enhance consumer trust and positive attitude toward the sharing economy platform (Wang and Jeong, 2018). All these enhance consumer purchase behavior.

One of the biggest concerns of consumers and the source of perceived risk in sharing economy lies in the fact of lacking regulation (Sutherland and Jarrahi, 2018). Provider verification can be viewed as a strong indicator that the platform aims to achieve its long-term sustainable operations through enforcing strict regulations on the suppliers (Xie and Mao, 2017). This enhances the perceived fairness and equity of the transaction from consumers' view, and improves the perceived security of the transaction (Wang and He, 2019). This enhances the image of the sharing economy platform, and thus enhance consumers' acceptance (Cherry and Pidgeon, 2018). Based on the preceding discussion, we propose the following hypothesis:

H5. Posting provider verification information enhances consumer purchase behavior.

3.2.6. The influence of consumer ratings on consumer purchase behavior

Consumer ratings reflect their evaluation and overall satisfaction of the whole consumption experience (Subramanian and Subramanyam, 2012). Consumers' ratings can generate electronic word of mouth effect, which influence future consumers' attitude toward the products and suppliers, and thus influence their purchase intention and behavior (Xu et al., 2017a). Higher ratings show providers' better reputation, which generates consumers' trust (Ert et al., 2016). Higher ratings also indicate the higher quality and value of the products and service, which stimulates consumers' purchase intention and behavior (Pang et al., 2015). Therefore, based on the above discussion, we hypothesize:

H6. Higher consumer ratings enhance consumer purchase behavior.

4. Data analysis

4.1. Data collection

Accommodation sharing industry is one of the most common and typical form of sharing economy context (Ert et al., 2016). Thus, in this study, referring to previous studies (e.g., Bae et al., 2017; Blal et al., 2018), we used accommodation sharing to reflect collaborative consumption. Following previous studies (e.g., Brochado et al., 2017; Li and Srinivasan, 2019; Roma et al., 2019), we collected data from the world largest accommodation sharing platform Airbnb. Since its launch in San Francisco in 2008, Airbnb has rapid growth during the past decade, and has now covered 65,000 cities over the world with an estimated current market value of $30 billion (Cheng and Jin, 2019). Under the Airbnb context, providers are the hosts, who provide both the products (e.g., room and its amenities) and services (e.g., cleaning and maintenance), and interact with consumers. Sharing economy consumers here are the guests potentially to stay in the hosts' rooms. For Airbnb, the peer consumers are the peer guests. They either share the room or building with other guests or interact with other guests through the sharing economy platform.

We implemented a web crawler in Java to collect data from Airbnb website directly in May 2017. The search criterion we used for all cities are: a single adult searches for a room to stay from December 1, 2017 to December 4, 2017. Specifically, our web crawler searches for the room listings that satisfy our designed search criterion, and then extracts data from the web pages of room listings and their hosts.

Our search criteria include two components: time (i.e., check-in and check-out date) and number of guests. Airbnb only show the available listing (i.e., the accommodation that haven't been booked) after the search criteria are input (Airbnb Help Center, 2020). Thus, the search criteria used for this study are intended to maximize the number of room listings that we can collect.

Regarding the check-in date criterion, it was chosen to be far enough into the future so that most of the available rooms haven't been booked yet. At the same time, most of the hosts may only be certain about their rooms' availability into the near future, and thus the check-in date selected should not be too far from the search date. A few rounds of pilot data collection showed it is better to gather the data about seven to eight months ahead of the targeted check-in date to balance such tradeoffs. For the stay length, previous researches (e.g., Pillow, 2019) found on average the stay period for an accommodation lasts for three nights after removing outliers that significantly skew the trip length. Our search criteria align with such average stay period for an accommodation. Regarding the number of guests, we chose a single adult in our search criteria trying to maximize the room listings displayed.

Although the data we have collected represent a snapshot of the website, most of the information in our analysis aims to capture the long-term characteristics of room listings and hosts, such as the product (i.e., room) and social information provided by the hosts, information provided by the platforms, and average consumer ratings. And the information disclosure pattern does not alter frequently over time. Therefore, we expect that the selected search criteria in our study provide us some unbiased observations on the impact of information disclosure strategies.

Within each city of interest, our web crawler focuses on each of the neighborhoods defined by Airbnb. All the information we collected is publicly available to all consumers who visit Airbnb website. Each of our datasets contains large number of room listings from a single city in the United States. We noticed that Airbnb displays no more than 306 available room listings that match any given search criteria (that is, 18 room listings per page, 17 pages maximum). In order to collect as many room listings as possible, in addition to city and check-in/check-out dates, we added neighborhood – a finer geographic partition of a city defined by Airbnb – to our search criteria, one at a time following the list of neighborhoods provided by Airbnb for each city. Our final data set contains eight major cities in United States with 8804 complete observations in total covering the different geographical locations of U.S. (namely, western coast, eastern coast, mid-west, and south). These eight cities are as follows: Boston (384 accommodations in 27 neighborhoods), Chicago (599 accommodations in 37 neighborhoods), Los Angeles (2629 accommodations in 103 neighborhoods), New Orleans (613 accommodations in 30 neighborhoods), New York (2101 accommodations in 99 neighborhoods) San Francisco (1003 accommodations in 83 neighborhoods), Seattle (776 accommodations in 58 neighborhoods), and Washington D.C (699 accommodations in 65 neighborhoods).

4.2. Dependent variable

Given the features and availability of the secondary data, referring to previous studies examining the influence of information disclosure on online consumers' shopping behavior (e.g., Subramanian and Subramanyam, 2012; Pang et al., 2015; Xu et al., 2017b), in this study, we use multivariate regression to test the relationship between information disclosure and consumers' purchase behavior.

A challenge met by many previous studies using secondary data is the unavailability of the detailed booking data to show product sales (e. g., Ghose and Ipeirotis, 2006). Previous studies used various approaches to find a proxy for product sales (i.e., consumer demand), including sales ranks (e.g., Chevalier and Mayzlin, 2006; Ghose and Ipeirotis, 2006); number of online consumer reviews (Ye et al., 2009, 2011), and number of page views (Zhang et al., 2010).

In this study, we were not able to observe the actual accommodation bookings from Airbnb.com, as these are the private data of the individual owner concerned. Referring to previous studies (e.g., Ye et al., 2009; Ye et al., 2011; Xu, 2020), we used the number of online reviews as a proxy for the sales. The rationale of our assumption that the number of room sales has a linear relationship with the number of online reviews (i.e., Number of Reviews $= \varphi\times$ Number of Bookings, where $0\% < \varphi < 100\%$) is as follows. First, in our study, the feature of Airbnb that allows only consumers who book accommodations through its website to post reviews within 14 days is leveraged. Thus, the number of room sales is expected to be closely correlated to the number of consumer reviews (Ye et al., 2011). Second, previous studies (e.g., Ye et al., 2009) found the probability for consumers to post reviews on a booking website is stable across the accommodations. This reduces the heterogeneity effect caused by different accommodations. Thus, the larger amount of online reviews shows more popularity of a room listing, meaning more consumer demand and showing more consumer purchase behavior. Third, in sharing economy, because of the properties of collaborative consumptions, the motivation for consumers to post their reviews after their stay is high – to interact with the other participants, including hosts and other consumers, and to meet their psychological and social needs to reveal their emotion and communicate with others (Cheng and Jin, 2019). Consumers also have the altruism motivation to post their reviews wanting to provide detailed information about their consumption experience to others (Cheung and Lee, 2012). This is particular true due to the uniqueness of products and services in sharing economy contexts and consumers' lack of knowledge about them (So et al., 2018). Thus, this extends the generality of the number of online consumer reviews in reflecting room sales (Xu, 2020). Observing the skewness of the value of Number of Online Reviews (*Room.Number.Reviews*), following previous studies (e.g., Ye et al., 2009; Ye et al., 2011; Zhang et al., 2010), we use its natural logarithm as the dependent variable (log*(Room.Number.Reviews)*) in our regression analysis.

4.3. Measurements of information in each category

Referring to previous studies (e.g., Xu et al., 2017a, 2017b), for each of the six categories of information introduced in Section 3, we use some representative variables in our datasets to reflect those categories respectively. We introduce the variables by their types below, where the names in parentheses are used as variable names in our empirical model in Section 5.

4.3.1. Measurements of product information

The core product of accommodation offering is the room (Guttentag and Smith, 2017), and thus the measurements of product information focus on the key features of the room. Two variables describing main characteristics of rooms are included here. Number of Room Photos (*Room.Number.Photos*) is a non-negative integer variable that describes the number of room photos displayed on the room listing page and may contain (but not limited to) the inside and outside of the room. Number of room photos represents the amount of a room's visual information provided by its host. Room Description Length (*Room.Description.Length*) is a non-negative integer variable of the length (in characters) of the entire room description section on room listing pages, which represents the amount of room text information provided by its host. Observing the skewness of the value of Room.Description.Length, we use its natural logarithm (log*(Room.Description.Length)*) as an independent variable in our regression analysis.

4.3.2. Measurements of hosts' social identity information

Measurements of hosts' social identity information is the self-revealed information about hosts, which includes three variables. Number of Host Photos (*Host.Number.Photos*) is a non-negative integer variable that describes the number of a host's personal photos displayed on profile pages. It represents the amount of visual information that the host(s) reveal. According to our observations, some of the photos do not include the host(s). Observing the skewness of this variable, we use its natural logarithm (log*(Host.Number.Photos)*) in our regression analysis. Host Description Length (*Host.Description.Length*) is a non-negative integer variable of the length (in characters) of the host's description section on his/her profile page. Observing the skewness of the values of host description length, we use its natural logarithm (log*(Host.Description.Length)*) in our regression analysis.

Host Gender Composition (*Host.Gender*) is a categorical variable that describes the gender(s) of the host(s). Consumer can identify the gender composition of the host(s) by examining the first names and photos of the host(s) although such information is not explicitly available on Airbnb pages. Our web crawler identifies the gender composition of hosts by cross-referencing their first names against a first name-gender database provided by the Open Gender Tracking Project (initiated by the MIT Center for Civic Media). The name-gender library includes 125,667 names, and each may be used as either a male first name or a female first name. For each name, its frequencies of being used as a male first name and as a female first name are recorded separately. The probability of a name being a male first name or female first name is computed as the proportion of the two corresponding frequencies. Our web crawler labels a first name as a male's first name if it is used as a male's first name at least 60% of probability based on the data from the first name-gender database. A first name is determined as a female's first name in similar way. By choosing 60% as the threshold, we ruled out the 1% of the first names with the highest degree of gender ambiguity (with less than 60% of probability being used as either a male first name or a female first name) while keeping the rest 99% of the first names to maximize the probabilities of matching the first names observed in our Airbnb datasets. Similar methods have been used in previous studies (e.g., Liu and Ruths, 2013) to determine the probability of a first name being used as either a male first name or a female first name. As a result, we discovered five host gender composition types in all eight datasets: single male host (*Host.Gender.MALE*), single female host (*Host.Gender.FEMALE*), one male host and one female host (*Host.Gender.MALE + FEMALE*), two male hosts (*Host.Gender.MALE + MALE*), and two female hosts (*Host.Gender.FEMALE + FEMALE*). We represent host gender composition by four dummy variables that correspond to the last four types with *Host.Gender.MALE* as the baseline.

4.3.3. Measurements of host-consumer interaction information

Measurements of host-consumer interaction information shows the social network relationship and interactions between seller and buyer, which includes five variables. Response Rate (*Host.Response.Rate*) is a numeric variable between 0 and 100 that represents the percentage of guests' inquiries ever responded by a host. A higher response rate may imply a more responsive host. Observing the skewness of the value of *Host.Response.Rate*, we use its natural logarithm (log*(Host.Response.Rate)*) as an independent variable in our regression analysis. Response Time (*Host.Response.Time*) is a categorical variable that describes the average timeliness of a host's responses to guests' inquiries. Airbnb categorizes a host's average response time into four types: within an hour (*Host.Response.Time.within an hour*), within a few hours (*Host.Response.Time.within a few hours*), within a day (*Host.Response.Time.within a day*), and a few days or more (*Host.Response.Time.a few days or more*). In our regression analysis, response time is represented by three dummy variables that correspond to the last three types, with *Host.Response.Time.within an hour* as the baseline. Facebook Connection (*Host.Facebook*), Google Connection (*Host.Google*) and LinkedIn Connection (*Host.LinkedIn*) are three dummy variables that indicate whether the links to the host's Facebook page, Google page, and LinkedIn page have been displayed on host's profile page on Airbnb.com. Posting these links shows hosts' willingness to have presence in online social networks, both personally and professionally. It also shows their incentives to have online communications with consumers and other participants in the online community.

4.3.4. Measurements of platform recommendation information

In order to facilitate transactions between potential guests and hosts, Airbnb.com's proprietary algorithm identifies and brands some of the room listing pages with so-called "hot room icons" in order to promote these rooms. Hot Room Icon of Room (*Room.Hot.Room.Icon*) is a categorical variable that captures the existence and type of hot room icons on a room listing page. We have observed a total of five different icons in room listings across eight datasets. Different icons have different meanings: Recently Viewed icon (*Room.Hot.Room.Icon.recently viewed*) means the room was recently viewed by some guests; Recently Booked icon (*Room.Hot.Room.Icon.recently booked*) means the room has recently been booked; Frequently Viewed icon (*Room.Hot.Room.Icon.frequently viewed*) means the room has been viewed frequently by guests; Frequently Booked (*Room.Hot.Room.Icon.frequently booked*) means the room is usually occupied; Great Value icon (*Room.Hot.Room.Icon.great value*) means the platform recommends this accommodation as having relatively high value for money. Many room listings are not branded with any icon (*Room.Hot.Room.Icon.null*), which is the baseline. Note that for some cities, not all five icons were observed among the room listings.

4.3.5. Measurements of host verification information

Provider verification information includes two variables. Verified using Personal Information (*Host.Verified.Personal.Info*) and Verified using Government Issued ID (*Host.Verified.ID*) are dummy variables indicating whether the hosts have been verified by Airbnb using corresponding information. These variables being true sends trust signals to guests, as the Airbnb platform verifies the hosts' information.

4.3.6. Measurements of guests' overall ratings information

Guests' overall rating information is measured by Overall Room Rating (*Room.Overall.Rating*), which is a numeric variable between 1 and 5 that represents the average rating score of a room listing, with 1 being the worst 5 being the best. Overall Room Rating reflects consumers' overall perception and evaluation toward the consumption experience.

4.4. Control variables

We include five type of control variables in our study. The first is the unit price per guest. The detailed price breakdown contains room cost, one-time cleaning fee, service fee, and occupancy taxes, which are displayed on the room listing page. We calculate the unit price per guest by dividing a room's total price by the number of days of the reservation, and then by the number of guests it accommodates. It is possible that different neighborhoods have different levels of demand within the same city, depending on the nature of the neighborhood and places of interests. For example, a neighborhood that has more tourist attractions or is located in a convenient geographical location may attract greater demand compared to other neighborhoods, resulting in higher unit price per guest on average. To eliminate such individual neighborhood effects, we normalize the unit price per guest within each neighborhood such that it is a numeric value between 0 and 100, which is referred as the Normalized Unit Price per Guest (*Room.Normalized.Unit.Price*).

Second, intuitively, the longer a host has been active on Airbnb, the higher chance that his/her rooms may have collected a greater Number of Reviews. Hosts' Tenure (*Host.Tenure*) is a non-negative integer variable that represents the number of months a host has been active on Airbnb, which can be calculated from the join date displayed on the host's profile page. Observing the skewness of the value of Host.Tenure, we use its natural logarithm (log*(Host.Tenure)*) as an independent variable in our regression analysis.

Third, Number of Rooms Hosted (*Host.Room.Number*) is a positive integer variable that specifies the number of rooms that a particular host is advertising on Airbnb at the time of data collection. Our web crawler extracts this information by matching the host ID of different room listings. Although this information is not directly available to consumers, it can be obtained relatively easy by skimming through the room listings and the host's profile page. A greater number of rooms hosted by the same host may be an indicator of a professional Airbnb host, who dedicates most of his/her time to Airbnb services.

Fourth, to control the effect of various room types on consumer purchase behavior, we added Room Type (*Room.Type*) as a control variable. We have observed three types of rooms: Shared Room (*Room.Type.Shared room*), Private Room (*Room.Type.Private room*), and Entire Home or Apartment (*Room.Type.Entire home/apt*). From guests' point of view, shared rooms provide the least privacy while entire homes or apartments provide the most privacy. In our regression analysis, room type is represented by two dummy variables corresponding to the last two types with *Room.Type.Shared room* as baseline. To control the effect of room size on consumers' purchasing behavior, we added Number of Guests Accommodated (*Room.Accommodates*) as a control variable, which is a non-negative integer value that reflects the room size.

Lastly, our empirical analysis controls the effects from different neighborhoods and cities. As a common practice in econometric analysis, we controlled the effects of different neighborhoods on demand in the same city by adding neighborhood dummy variables (Kakar et al., 2018; Kitamura et al., 1997; Schuetz et al., 2008). However, for conciseness reasons, we did not present the results of these dummy variables (available upon the request) in our result Tables. Regarding the different cities and referring to previous studies (e.g., Abu-Lughod, 1995; Al Shehhi and Karathanasopoulos, 2020; Giglio et al., 2019; Haughwout et al., 2004; Romero et al., 2019), we control the effects through building separate models for each of the eight cities. In this way, we can solve the potential issues that the relationships between the independent variables and the dependent variable may be different across cities.

4.5. Summary statistics

The summary statistics of all the variables with outliers removed for the eight cities are provided in Table 1a–h. From the summary statistics, it can be found that the number of reviews garnered by the room listings within each city could range from a few to a couple hundreds, with the mean varying between 30 and 55, indicating that our datasets are good representations of both popular and unpopular room listings. For the product information, some of the hosts provide a great amount of information (visual and text) to consumers. On average, about 15–20 photos and a paragraph of room description with 1500 to 2000 characters in length are provided in a room listing.

For the provider's social identity information, on average hosts provide around 2 photos and a paragraph of self-description about 250–400 characters in length. Over 90% of the hosts are single judged by their profile pages. Regarding the gender composition, overall for the eight cities we observe the similar number of female hosts as male hosts. The remaining around 10% of the hosts are couples, of either different genders or of the same gender.

For the host-consumer interaction information, the average response rate to consumers' inquiries is 98%. Around 60%–70% of the consumers' inquiries are responded within a few hours. Although about 25% of the hosts provide links to their personal social network page (Facebook) on their profile pages, only less than 7% of the hosts provide links to their professional social network page (Google and LinkedIn).

Platform recommendation information suggests 0.3% accommodations are recently booked, 43% are frequently booked, 15% are recently viewed, 2% are frequently viewed, 9.7% are of great value, and the remaining 30% accommodations have no recommendation information displayed.

For the host verification information, 30%–50% of the hosts allowed Airbnb to conduct an identity verification using either personal information collected by various government agencies, or government issued

Table 1a
Descriptive statistics – Boston, MA

	Min	Max	Mean	Stdev	Median
Room.Number.Reviews	3.000	181.000	48.862	43.405	33.000
Room.Number.Photos	2.000	40.000	15.716	8.082	15.000
Room.Description.Length	111.000	5920.000	1823.708	1262.103	1587.000
Room.Type.Shared room	0.000	1.000	0.008	0.088	0.000
Room.Type.Entire home/apt	0.000	1.000	0.487	0.500	0.000
Room.Type.Private room	0.000	1.000	0.505	0.501	1.000
Room.Accommodates	1.000	10.000	3.214	1.978	2.000
Room.Normalized.Unit.Price	0.000	1.000	0.410	0.290	0.353
Room.Overall.Rating	3.000	5.000	4.720	0.338	5.000
Room.Hot.Room.Icon.null	0.000	1.000	0.365	0.482	0.000
Room.Hot.Room.Icon.recently booked	0.000	1.000	0.021	0.143	0.000
Room.Hot.Room.Icon.great value	0.000	1.000	0.521	0.500	1.000
Room.Hot.Room.Icon.recently viewed	0.000	1.000	0.094	0.292	0.000
Host.Number.Photos	1.000	6.000	1.872	1.263	1.000
Host.Description.Length	1.000	1180.000	357.000	260.172	303.000
Host.Response.Rate	33.000	100.000	98.141	6.527	100.000
Host.Response.Time.within an hour	0.000	1.000	0.745	0.437	1.000
Host.Response.Time.a few days or more	0.000	1.000	0.005	0.072	0.000
Host.Response.Time.within a day	0.000	1.000	0.063	0.242	0.000
Host.Response.Time.within a few hours	0.000	1.000	0.188	0.391	0.000
Host.Verified.ID	0.000	1.000	0.323	0.468	0.000
Host.Verified.Personal.Info	0.000	1.000	0.552	0.498	1.000
Host.Gender.MALE	0.000	1.000	0.466	0.500	0.000
Host.Gender.FEMALE	0.000	1.000	0.479	0.500	0.000
Host.Gender.FEMALE + FEMALE	0.000	1.000	0.013	0.114	0.000
Host.Gender.MALE + FEMALE	0.000	1.000	0.036	0.188	0.000
Host.Gender.MALE + MALE	0.000	1.000	0.005	0.072	0.000
Host.Tenure	24.000	120.000	62.698	22.507	59.000
Host.Facebook	0.000	1.000	0.232	0.423	0.000
Host.Google	0.000	1.000	0.073	0.260	0.000
Host.LinkedIn	0.000	1.000	0.034	0.181	0.000
Host.Room.Number	1.000	10.000	2.565	2.066	2.000

Table 1b
Descriptive statistics – Chicago, IL

	Min	Max	Mean	Stdev	Median
Room.Number.Reviews	3.000	148.000	39.671	34.556	27.000
Room.Number.Photos	2.000	43.000	16.644	8.632	15.000
Room.Description.Length	82.000	4960.000	1769.232	1045.974	1603.000
Room.Type.Shared room	0.000	1.000	0.013	0.115	0.000
Room.Type.Entire home/apt	0.000	1.000	0.546	0.498	1.000
Room.Type.Private room	0.000	1.000	0.441	0.497	0.000
Room.Accommodates	1.000	10.000	3.866	2.222	3.000
Room.Normalized.Unit.Price	0.000	0.976	0.313	0.234	0.259
Room.Overall.Rating	2.500	5.000	4.796	0.306	5.000
Room.Hot.Room.Icon.null	0.000	1.000	0.382	0.486	0.000
Room.Hot.Room.Icon.frequently booked	0.000	1.000	0.492	0.500	0.000
Room.Hot.Room.Icon.recently viewed	0.000	1.000	0.125	0.331	0.000
Host.Number.Photos	1.000	6.000	1.918	1.175	2.000
Host.Description.Length	6.000	1138.000	331.042	236.414	279.000
Host.Response.Rate	50.000	100.000	97.866	6.601	100.000
Host.Response.Time.within an hour	0.000	1.000	0.688	0.464	1.000
Host.Response.Time.within a day	0.000	1.000	0.090	0.287	0.000
Host.Response.Time.within a few hours	0.000	1.000	0.222	0.416	0.000
Host.Verified.ID	0.000	1.000	0.367	0.482	0.000
Host.Verified.Personal.Info	0.000	1.000	0.514	0.500	1.000
Host.Gender.MALE	0.000	1.000	0.476	0.500	0.000
Host.Gender.FEMALE	0.000	1.000	0.462	0.499	0.000
Host.Gender.FEMALE + FEMALE	0.000	1.000	0.005	0.071	0.000
Host.Gender.MALE + FEMALE	0.000	1.000	0.040	0.196	0.000
Host.Gender.MALE + MALE	0.000	1.000	0.017	0.128	0.000
Host.Tenure	24.000	115.000	56.980	19.364	54.000
Host.Facebook	0.000	1.000	0.260	0.439	0.000
Host.Google	0.000	1.000	0.077	0.266	0.000
Host.LinkedIn	0.000	1.000	0.045	0.208	0.000
Host.Room.Number	1.000	6.000	1.628	1.044	1.000

Table 1c
Descriptive statistics – Los Angeles, CA

	Min	Max	Mean	Stdev	Median
Room.Number.Reviews	3.000	153.000	40.275	36.114	28.000
Room.Number.Photos	2.000	53.000	19.873	10.508	18.000
Room.Description.Length	52.000	5938.000	1772.272	1228.453	1528.000
Room.Type.Shared room	0.000	1.000	0.014	0.116	0.000
Room.Type.Entire home/apt	0.000	1.000	0.600	0.490	1.000
Room.Type.Private room	0.000	1.000	0.386	0.487	0.000
Room.Accommodates	1.000	10.000	3.389	1.925	3.000
Room.Normalized.Unit.Price	0.000	0.797	0.271	0.184	0.234
Room.Overall.Rating	2.500	5.000	4.812	0.289	5.000
Room.Hot.Room.Icon.null	0.000	1.000	0.452	0.498	0.000
Room.Hot.Room.Icon.recently booked	0.000	1.000	0.000	0.020	0.000
Room.Hot.Room.Icon.frequently viewed	0.000	1.000	0.003	0.052	0.000
Room.Hot.Room.Icon.frequently booked	0.000	1.000	0.332	0.471	0.000
Room.Hot.Room.Icon.recently viewed	0.000	1.000	0.213	0.410	0.000
Host.Number.Photos	1.000	6.000	1.976	1.326	1.000
Host.Description.Length	1.000	1014.000	298.633	220.374	248.000
Host.Response.Rate	50.000	100.000	98.013	6.075	100.000
Host.Response.Time.within an hour	0.000	1.000	0.736	0.441	1.000
Host.Response.Time.within a day	0.000	1.000	0.060	0.238	0.000
Host.Response.Time.within a few hours	0.000	1.000	0.204	0.403	0.000
Host.Verified.ID	0.000	1.000	0.435	0.496	0.000
Host.Verified.Personal.Info	0.000	1.000	0.428	0.495	0.000
Host.Gender.MALE	0.000	1.000	0.402	0.490	0.000
Host.Gender.FEMALE	0.000	1.000	0.542	0.498	1.000
Host.Gender.FEMALE + FEMALE	0.000	1.000	0.007	0.085	0.000
Host.Gender.MALE + FEMALE	0.000	1.000	0.041	0.198	0.000
Host.Gender.MALE + MALE	0.000	1.000	0.008	0.087	0.000
Host.Tenure	23.000	120.000	58.137	19.214	57.000
Host.Facebook	0.000	1.000	0.248	0.432	0.000
Host.Google	0.000	1.000	0.075	0.264	0.000
Host.LinkedIn	0.000	1.000	0.023	0.151	0.000
Host.Room.Number	1.000	6.000	1.995	1.395	1.000

Table 1d
Descriptive statistics – New Orleans, LA

	Min	Max	Mean	Stdev	Median
Room.Number.Reviews	3.000	148.000	41.184	35.723	30.000
Room.Number.Photos	2.000	46.000	16.413	8.657	15.000
Room.Description.Length	63.000	5824.000	1801.305	1237.980	1555.000
Room.Type.Shared room	0.000	1.000	0.007	0.081	0.000
Room.Type.Entire home/apt	0.000	1.000	0.754	0.431	1.000
Room.Type.Private room	0.000	1.000	0.240	0.427	0.000
Room.Accommodates	1.000	10.000	4.152	2.082	4.000
Room.Normalized.Unit.Price	0.000	0.817	0.277	0.185	0.247
Room.Overall.Rating	3.000	5.000	4.840	0.260	5.000
Room.Hot.Room.Icon.null	0.000	1.000	0.656	0.475	1.000
Room.Hot.Room.Icon.recently booked	0.000	1.000	0.003	0.057	0.000
Room.Hot.Room.Icon.frequently booked	0.000	1.000	0.186	0.389	0.000
Room.Hot.Room.Icon.recently viewed	0.000	1.000	0.155	0.362	0.000
Host.Number.Photos	1.000	6.000	1.863	1.236	1.000
Host.Description.Length	5.000	1003.000	315.703	232.002	273.000
Host.Response.Rate	17.000	100.000	98.192	6.534	100.000
Host.Response.Time.within an hour	0.000	1.000	0.706	0.456	1.000
Host.Response.Time.a few days or more	0.000	1.000	0.002	0.040	0.000
Host.Response.Time.within a day	0.000	1.000	0.098	0.297	0.000
Host.Response.Time.within a few hours	0.000	1.000	0.194	0.396	0.000
Host.Verified.ID	0.000	1.000	0.307	0.461	0.000
Host.Verified.Personal.Info	0.000	1.000	0.525	0.500	1.000
Host.Gender.MALE	0.000	1.000	0.432	0.496	0.000
Host.Gender.FEMALE	0.000	1.000	0.512	0.500	1.000
Host.Gender.FEMALE + FEMALE	0.000	1.000	0.003	0.057	0.000
Host.Gender.MALE + FEMALE	0.000	1.000	0.036	0.186	0.000
Host.Gender.MALE + MALE	0.000	1.000	0.016	0.127	0.000
Host.Tenure	23.000	114.000	58.551	18.081	57.000
Host.Facebook	0.000	1.000	0.259	0.439	0.000
Host.Google	0.000	1.000	0.042	0.202	0.000
Host.LinkedIn	0.000	1.000	0.011	0.106	0.000
Host.Room.Number	1.000	6.000	1.838	1.329	1.000

Table 1e
Descriptive statistics – New York, NY.

	Min	Max	Mean	Stdev	Median
Room.Number.Reviews	3.000	153.000	45.388	36.662	36.000
Room.Number.Photos	2.000	45.000	16.231	8.605	15.000
Room.Description.Length	40.000	4932.000	1639.880	1034.671	1471.000
Room.Type.Shared room	0.000	1.000	0.019	0.135	0.000
Room.Type.Entire home/apt	0.000	1.000	0.549	0.498	1.000
Room.Type.Private room	0.000	1.000	0.432	0.495	0.000
Room.Accommodates	1.000	10.000	3.453	2.017	3.000
Room.Normalized.Unit.Price	0.000	0.893	0.311	0.197	0.283
Room.Overall.Rating	2.500	5.000	4.682	0.329	4.500
Room.Hot.Room.Icon.null	0.000	1.000	0.279	0.449	0.000
Room.Hot.Room.Icon.recently booked	0.000	1.000	0.001	0.031	0.000
Room.Hot.Room.Icon.frequently viewed	0.000	1.000	0.012	0.111	0.000
Room.Hot.Room.Icon.frequently booked	0.000	1.000	0.557	0.497	1.000
Room.Hot.Room.Icon.recently viewed	0.000	1.000	0.150	0.358	0.000
Host.Number.Photos	1.000	6.000	1.907	1.285	1.000
Host.Description.Length	1.000	885.000	260.091	195.474	222.000
Host.Response.Rate	17.000	100.000	97.134	7.907	100.000
Host.Response.Time.within an hour	0.000	1.000	0.646	0.478	1.000
Host.Response.Time.a few days or more	0.000	1.000	0.004	0.065	0.000
Host.Response.Time.within a day	0.000	1.000	0.094	0.292	0.000
Host.Response.Time.within a few hours	0.000	1.000	0.256	0.436	0.000
Host.Verified.ID	0.000	1.000	0.410	0.492	0.000
Host.Verified.Personal.Info	0.000	1.000	0.393	0.489	0.000
Host.Gender.MALE	0.000	1.000	0.491	0.500	0.000
Host.Gender.FEMALE	0.000	1.000	0.467	0.499	0.000
Host.Gender.FEMALE + FEMALE	0.000	1.000	0.009	0.095	0.000
Host.Gender.MALE + FEMALE	0.000	1.000	0.027	0.161	0.000
Host.Gender.MALE + MALE	0.000	1.000	0.007	0.081	0.000
Host.Tenure	23.000	121.000	60.665	21.106	59.000
Host.Facebook	0.000	1.000	0.226	0.418	0.000
Host.Google	0.000	1.000	0.061	0.239	0.000
Host.LinkedIn	0.000	1.000	0.027	0.163	0.000
Host.Room.Number	1.000	3.000	1.354	0.640	1.000

Table 1f
Descriptive statistics – San Francisco, CA

	Min	Max	Mean	Stdev	Median
Room.Number.Reviews	3.000	190.000	54.278	46.148	40.000
Room.Number.Photos	2.000	46.000	16.931	8.875	15.000
Room.Description.Length	71.000	5654.000	1958.548	1182.961	1773.000
Room.Type.Shared room	0.000	1.000	0.010	0.099	0.000
Room.Type.Entire home/apt	0.000	1.000	0.524	0.500	1.000
Room.Type.Private room	0.000	1.000	0.466	0.499	0.000
Room.Accommodates	1.000	10.000	2.998	1.751	2.000
Room.Normalized.Unit.Price	0.000	0.851	0.290	0.196	0.256
Room.Overall.Rating	2.500	5.000	4.831	0.279	5.000
Room.Hot.Room.Icon.null	0.000	1.000	0.381	0.486	0.000
Room.Hot.Room.Icon.frequently booked	0.000	1.000	0.505	0.500	1.000
Room.Hot.Room.Icon.recently viewed	0.000	1.000	0.114	0.318	0.000
Host.Number.Photos	1.000	3.000	1.507	0.684	1.000
Host.Description.Length	2.000	1116.000	334.176	245.378	276.000
Host.Response.Rate	10.000	100.000	98.308	6.443	100.000
Host.Response.Time.within an hour	0.000	1.000	0.622	0.485	1.000
Host.Response.Time.a few days or more	0.000	1.000	0.002	0.045	0.000
Host.Response.Time.within a day	0.000	1.000	0.104	0.305	0.000
Host.Response.Time.within a few hours	0.000	1.000	0.272	0.445	0.000
Host.Verified.ID	0.000	1.000	0.325	0.469	0.000
Host.Verified.Personal.Info	0.000	1.000	0.533	0.499	1.000
Host.Gender.MALE	0.000	1.000	0.378	0.485	0.000
Host.Gender.FEMALE	0.000	1.000	0.565	0.496	1.000
Host.Gender.FEMALE + FEMALE	0.000	1.000	0.008	0.089	0.000
Host.Gender.MALE + FEMALE	0.000	1.000	0.036	0.186	0.000
Host.Gender.MALE + MALE	0.000	1.000	0.013	0.113	0.000
Host.Tenure	23.000	117.000	64.465	20.249	64.000
Host.Facebook	0.000	1.000	0.245	0.430	0.000
Host.Google	0.000	1.000	0.032	0.176	0.000
Host.LinkedIn	0.000	1.000	0.022	0.147	0.000
Host.Room.Number	1.000	3.000	1.362	0.620	1.000

Table 1g
Descriptive statistics – Seattle, WA

	Min	Max	Mean	Stdev	Median
Room.Number.Reviews	3.000	172.000	48.284	40.462	35.000
Room.Number.Photos	2.000	43.000	16.543	8.259	15.000
Room.Description.Length	64.000	6066.000	2043.715	1212.705	1862.500
Room.Type.Shared room	0.000	1.000	0.004	0.062	0.000
Room.Type.Entire home/apt	0.000	1.000	0.671	0.470	1.000
Room.Type.Private room	0.000	1.000	0.325	0.469	0.000
Room.Accommodates	1.000	10.000	3.497	1.824	3.000
Room.Normalized.Unit.Price	0.000	0.960	0.300	0.223	0.256
Room.Overall.Rating	3.500	5.000	4.840	0.258	5.000
Room.Hot.Room.Icon.null	0.000	1.000	0.317	0.466	0.000
Room.Hot.Room.Icon.recently booked	0.000	1.000	0.006	0.080	0.000
Room.Hot.Room.Icon.frequently viewed	0.000	1.000	0.001	0.036	0.000
Room.Hot.Room.Icon.great value	0.000	1.000	0.575	0.495	1.000
Room.Hot.Room.Icon.recently viewed	0.000	1.000	0.101	0.301	0.000
Host.Number.Photos	1.000	4.000	1.653	0.868	1.000
Host.Description.Length	3.000	1331.000	398.834	262.202	352.000
Host.Response.Rate	25.000	100.000	97.854	7.956	100.000
Host.Response.Time.within an hour	0.000	1.000	0.653	0.476	1.000
Host.Response.Time.a few days or more	0.000	1.000	0.004	0.062	0.000
Host.Response.Time.within a day	0.000	1.000	0.094	0.292	0.000
Host.Response.Time.within a few hours	0.000	1.000	0.249	0.433	0.000
Host.Verified.ID	0.000	1.000	0.334	0.472	0.000
Host.Verified.Personal.Info	0.000	1.000	0.540	0.499	1.000
Host.Gender.MALE	0.000	1.000	0.390	0.488	0.000
Host.Gender.FEMALE	0.000	1.000	0.550	0.498	1.000
Host.Gender.FEMALE + FEMALE	0.000	1.000	0.008	0.088	0.000
Host.Gender.MALE + FEMALE	0.000	1.000	0.041	0.199	0.000
Host.Gender.MALE + MALE	0.000	1.000	0.010	0.101	0.000
Host.Tenure	22.000	123.000	61.412	20.604	59.000
Host.Facebook	0.000	1.000	0.298	0.458	0.000
Host.Google	0.000	1.000	0.045	0.208	0.000
Host.LinkedIn	0.000	1.000	0.023	0.151	0.000
Host.Room.Number	1.000	6.000	1.830	1.357	1.000

Table 1h
Descriptive statistics – Washington, D.C.

	Min	Max	Mean	Stdev	Median
Room.Number.Reviews	3.000	144.000	40.213	34.464	29.000
Room.Number.Photos	2.000	44.000	16.898	8.515	16.000
Room.Description.Length	53.000	6190.000	1866.492	1229.869	1601.000
Room.Type.Shared room	0.000	1.000	0.016	0.125	0.000
Room.Type.Entire home/apt	0.000	1.000	0.622	0.485	1.000
Room.Type.Private room	0.000	1.000	0.362	0.481	0.000
Room.Accommodates	1.000	10.000	3.557	1.993	3.000
Room.Normalized.Unit.Price	0.000	0.928	0.279	0.209	0.231
Room.Overall.Rating	3.500	5.000	4.811	0.281	5.000
Room.Hot.Room.Icon.null	0.000	1.000	0.413	0.493	0.000
Room.Hot.Room.Icon.recently booked	0.000	1.000	0.009	0.092	0.000
Room.Hot.Room.Icon.frequently booked	0.000	1.000	0.186	0.389	0.000
Room.Hot.Room.Icon.great value	0.000	1.000	0.290	0.454	0.000
Room.Hot.Room.Icon.recently viewed	0.000	1.000	0.102	0.302	0.000
Host.Number.Photos	1.000	6.000	1.924	1.238	1.000
Host.Description.Length	2.000	1170.000	344.582	265.263	282.000
Host.Response.Rate	20.000	100.000	97.894	6.951	100.000
Host.Response.Time.within an hour	0.000	1.000	0.631	0.483	1.000
Host.Response.Time.a few days or more	0.000	1.000	0.001	0.038	0.000
Host.Response.Time.within a day	0.000	1.000	0.113	0.317	0.000
Host.Response.Time.within a few hours	0.000	1.000	0.255	0.436	0.000
Host.Verified.ID	0.000	1.000	0.329	0.470	0.000
Host.Verified.Personal.Info	0.000	1.000	0.502	0.500	1.000
Host.Gender.MALE	0.000	1.000	0.456	0.498	0.000
Host.Gender.FEMALE	0.000	1.000	0.488	0.500	0.000
Host.Gender.FEMALE + FEMALE	0.000	1.000	0.007	0.084	0.000
Host.Gender.MALE + FEMALE	0.000	1.000	0.039	0.193	0.000
Host.Gender.MALE + MALE	0.000	1.000	0.010	0.100	0.000
Host.Tenure	24.000	116.000	58.358	19.384	56.000
Host.Facebook	0.000	1.000	0.226	0.419	0.000
Host.Google	0.000	1.000	0.064	0.246	0.000
Host.LinkedIn	0.000	1.000	0.037	0.189	0.000
Host.Room.Number	1.000	6.000	1.827	1.277	1.000

ID (driver's license, passport, and so on). For the overall ratings given by guests, on average each room listing receives an overall rating of 4.8.

For control variables, the average normalized unit price per guest is 0.3, the average length of time a host has been active on Airbnb is five years (60 months). On average, each host posts around 2 room listings on Airbnb, with only few professional hosts who post a maximum of 10 room listings. In terms of room type, 59% of the room listings s are entire homes or apartments, 39.5% of the room listings are private rooms, and the remaining 1.5% of the room listings are shared rooms. The number of guests accommodated ranges from 1 to 10, with an average of 3.5 guests per accommodation.

5. Results and discussions

5.1. Results

Previous studies found the non-linear influential factors of consumer purchase intention and behavior (e.g., Mittal and Kamakura, 2001; Everard and Galletta, 2005; Lee and Lee, 2012). Therefore, in this study, we examine the non-linear relationship between all numerical independent variables and consumer purchase behavior. Namely, we examined the effect of the square terms of the following variables: *Room.Description.Length*, *Room.Number.Photos*, *Host.Number.Photos*, *Host.Description.Length*, *Room.Overall.Rating*, and *Host.Tenure* on consumer purchase behavior. All the regression results from the eight cities are shown in Table 2a–h. We find the results from the eight cities are generally consistent, with some differences among cities. Our results support previous studies (e.g., Liang et al., 2017; Cheng et al., 2019) examining accommodation sharing in each city separately, which reflects the generality of sharing economy phenomena with uniqueness of each city taking into consideration.

5.2. Discussions

5.2.1. The impact of product information on consumer purchase behavior

From the regression models, it is found that for some cities (e.g., Los Angles, New Orleans, New York, San Francisco), the product (i.e., room) information influences consumer purchase behavior. In detail, for product (i.e., room) information, we find that the number of photos and the length of room description positively influence consumer purchase behavior, and such influence diminishes with additional photos and text description (which is captured by the negative coefficient of the corresponding square terms [i.e., log*(Room.Description.Length)ˆ2* and *Room.Number.Photoˆ2*]), which supports H1, namely, the relationship between the room information and consumer purchase behavior is concave. Posting more information using texts and visualization enhances consumers' familiarity of the products, enhances the perceived value and consumers' cognitive trust toward the products, and reduces the perceived risk (Neto et al., 2016; Xu et al., 2017b). However, the marginal effect is decreasing. Posting the first 100 characters and 10 photos describing the room has more positive effect compared with the next 100 characters and 10 photos. This could be due to two reasons. First, for similar information, consumers pay more attention and obtain more insights from the initial information source than the additional source (Pavlou and Dimoka, 2006; Gu and Ye, 2014). Second, consumers need to invest more time costs to explore the descriptions when there are more texts and photos, which reduces the perceived ease of use and convenience (Chen et al., 2010).

5.2.2. The impact of providers' social identity information on consumer purchase behavior

We found that for most of the cities (except Chicago), the relationship between hosts' social identity information (in terms of self-description text form and photos) and consumers' purchase behavior

Table 2a
Regression results – Boston, MA

Factors Category	Variables	Estimate (Std. Error)
	(Intercept)	−16.189 (8.2356)*
Product Information	log(Room.Description.Length)	0.3745 (0.7934)
	log(Room.Description.Length)ˆ2	−0.0033 (0.0572)
	Room.Number.Photos	0.0365 (0.0252)
	Room.Number.Photosˆ2	−0.0008 (0.0007)
Host Information	Host.Number.Photos	−0.0398 (0.1767)
	Host.Number.Photosˆ2	0.005 (0.0315)
	log(Host.Description.Length)	0.2256 (0.173)
	log(Host.Description.Length)ˆ2	−0.023 (0.0195)
	Host.Gender.FEMALE	0.0129 (0.1035)
	Host.Gender.FEMALE + FEMALE	0.2179 (0.253)
	Host.Gender.MALE + FEMALE	0.0105 (0.2611)
	Host.Gender.MALE + MALE	−0.8911 (1.0982)
Host-Consumer Interactions	log(Host.Response.Rate)	2.1222 (1.1604)*
	Host.Response.Time.a few days or more	1.0105 (1.4819)
	Host.Response.Time.within a day	−0.3929 (0.2279)*
	Host.Response.Time.within a few hours	0.0101 (0.141)
	Host.Facebook	0.1162 (0.1312)
	Host.Google	−0.3663 (0.2018)*
	Host.LinkedIn	−0.5766 (0.2405)**
Platform Recommendation	Room.Hot.Room.Icon.recently booked	0.8307 (0.2282)***
	Room.Hot.Room.Icon.great value	0.8959 (0.1105)***
	Room.Hot.Room.Icon.recently viewed	−0.173 (0.2152)
Host Verification	Host.Verified.ID	0.0584 (0.1364)
	Host.Verified.Personal.Info	−0.015 (0.1251)
Consumer Ratings	Room.Overall.Rating	1.5748 (2.2814)
	Room.Overall.Ratingˆ2	−0.1814 (0.2506)
Control Variables†	Room.Type.Entire home/apt	0.263 (0.2838)
	Room.Type.Private room	0.0401 (0.2791)
	Room.Accommodates	−0.1278 (0.0382)***
	Room.Normalized.Unit.Price	−0.6765 (0.2095)***
	log(Host.Tenure)	1.4262 (2.9412)
	log(Host.Tenure)ˆ2	−0.139 (0.3694)
	Host.Room.Number	−0.0525 (0.0334)

Remark.
*p < 0.1, **p < 0.05, ***p < 0.01 for all of Tables 2a – 2h.
† Dummy variables showing neighborhoods are included in the control variables. For conciseness reasons, we did not present the results of these dummy variables in Tables 2a – 2h.

Table 2b
Regression results – Chicago, IL

Factors Category	Variables	Estimate (Std. Error)
	(Intercept)	−16.9576 (5.3894)***
Product Information	log(Room.Description.Length)	0.0182 (0.595)
	log(Room.Description.Length)ˆ2	0.0213 (0.0433)
	Room.Number.Photos	0.0008 (0.0154)
	Room.Number.Photosˆ2	0.0001 (0.0003)
Host Information	Host.Number.Photos	0.2433 (0.1146)**
	Host.Number.Photosˆ2	−0.0457 (0.0206)**
	log(Host.Description.Length)	−0.0321 (0.3051)
	log(Host.Description.Length)ˆ2	−0.005 (0.03)
	Host.Gender.FEMALE	−0.1843 (0.0766)**
	Host.Gender.FEMALE + FEMALE	−0.2317 (0.4539)
	Host.Gender.MALE + FEMALE	−0.226 (0.1877)
	Host.Gender.MALE + MALE	−0.4165 (0.2488)*
Host-Consumer Interactions	log(Host.Response.Rate)	0.3767 (0.493)
	Host.Response.Time.within a day	−0.2809 (0.1498)*
	Host.Response.Time.within a few hours	−0.1486 (0.0858)*
	Host.Facebook	−0.1956 (0.0853)**
	Host.Google	−0.133 (0.1152)
	Host.LinkedIn	0.0188 (0.1283)
Platform Recommendation	Room.Hot.Room.Icon.frequently booked	0.9317 (0.0833)***
	Room.Hot.Room.Icon.recently viewed	0.1542 (0.1298)
Host Verification	Host.Verified.ID	0.0465 (0.0937)
	Host.Verified.Personal.Info	0.0467 (0.0955)
Consumer Ratings	Room.Overall.Rating	2.2635 (1.0123)**
	Room.Overall.Ratingˆ2	−0.2451 (0.1163)**
Control Variables	Room.Type.Entire home/apt	0.0535 (0.242)
	Room.Type.Private room	0.0802 (0.2325)
	Room.Accommodates	−0.0406 (0.0234)*
	Room.Normalized.Unit.Price	−0.2519 (0.1844)
	log(Host.Tenure)	6.211 (2.2675)***
	log(Host.Tenure)ˆ2	−0.7188 (0.2846)**
	Host.Room.Number	−0.1125 (0.0429)***

is not significant. This result does not support H2. One of the main reasons of this nonsignificant effect is because most of the text descriptions and photos are non-professional (e.g., describing the hosts' hobbies instead of their service), which might not help consumers know more about how much efforts the hosts put in for offering accommodation. The information quality, which is defined as the usefulness of the available information to help consumers evaluate the product or service provider (Gao et al., 2012), is relatively low in host identity information. This is reflected by that the hosts' self-disclosed information is subjective, has broad topics, reveals much about hosts' emotion, has too much sense of promotion, and is not much relevant to the offerings and their competitive advantage. Thus, this information can cause a distraction from relevant attributes and thus are not valued by consumers (Keller and Staelin, 1987).

In addition, we find that for some cities (e.g., Chicago, Los Angeles, New Orleans, San Francisco, Washington D.C.), the host(s) gender composition correlates with consumers' purchasing decisions. For example, holding all else equal, we observe a slightly higher demand for accommodations hosted by male and female couples compared to those hosted by a single male in Los Angeles, while accommodations hosted by same gender female couples are slightly preferred in San Francisco.

5.2.3. The impact of host-consumer interaction information on consumer purchase behavior

For host-consumer interactions, our results indicate that for most of the cities, hosts' responsiveness, which is reflected by their high response rate and fast response to consumers' inquires, enhances consumer purchase behavior. This supports H3a. Higher response rate and faster response speed show that the product/service supplier cares about consumers' experiences and needs, and demonstrate higher supplier willingness to improve the product and services, and make commitment on compensation as service recovery efforts if service failures occur, all

Table 2c
Regression results – Los Angeles, CA

Factors Category	Variables	Estimate (Std. Error)
	(Intercept)	−23.065 (4.4918)***
Product Information	log(Room.Description.Length)	0.088 (0.2529)
	log(Room.Description.Length)ˆ2	0.0049 (0.0183)
	Room.Number.Photos	0.0286 (0.0066)***
	Room.Number.Photosˆ2	−0.0004 (0.0001)***
Host Information	Host.Number.Photos	0.0245 (0.0527)
	Host.Number.Photosˆ2	−0.0062 (0.0087)
	log(Host.Description.Length)	0.0686 (0.0922)
	log(Host.Description.Length)ˆ2	−0.0032 (0.0096)
	Host.Gender.FEMALE	0.0127 (0.0362)
	Host.Gender.FEMALE + FEMALE	0.1883 (0.1564)
	Host.Gender.MALE + FEMALE	0.1577 (0.0792)**
	Host.Gender.MALE + MALE	0.0557 (0.2298)
Host-Consumer Interactions	log(Host.Response.Rate)	0.4742 (0.2557)*
	Host.Response.Time.within a day	−0.3049 (0.0826)***
	Host.Response.Time.within a few hours	−0.1771 (0.0435)***
	Host.Facebook	−0.0758 (0.0409)*
	Host.Google	−0.2801 (0.0675)***
	Host.LinkedIn	−0.2297 (0.1275)*
Platform Recommendation	Room.Hot.Room.Icon.recently booked	1.0392 (0.09)***
	Room.Hot.Room.Icon. frequently viewed	0.2756 (0.259)
	Room.Hot.Room.Icon. frequently booked	0.8748 (0.0441)***
	Room.Hot.Room.Icon.recently viewed	0.2886 (0.0534)***
Host Verification	Host.Verified.ID	0.0016 (0.0428)
	Host.Verified.Personal.Info	0.0434 (0.0439)
Consumer Ratings	Room.Overall.Rating	4.4746 (1.5893)***
	Room.Overall.Ratingˆ2	−0.494 (0.1718)***
Control Variables	Room.Type.Entire home/apt	0.054 (0.149)
	Room.Type.Private room	0.0094 (0.1437)
	Room.Accommodates	−0.0656 (0.0115)***
	Room.Normalized.Unit.Price	−0.5735 (0.1245)***
	log(Host.Tenure)	5.7312 (1.0887)***
	log(Host.Tenure)ˆ2	−0.6589 (0.1376)***
	Host.Room.Number	−0.0198 (0.0134)

Table 2d
Regression results – New Orleans, LA

Factors Category	Variables	Estimate (Std. Error)
	(Intercept)	−25.4055 (8.2093)***
Product Information	log(Room.Description.Length)	0.0339 (0.6741)
	log(Room.Description.Length)ˆ2	0.0129 (0.0478)
	Room.Number.Photos	0.0434 (0.0165)***
	Room.Number.Photosˆ2	−0.0009 (0.0004)**
Host Information	Host.Number.Photos	−0.0629 (0.107)
	Host.Number.Photosˆ2	0.0191 (0.0174)
	log(Host.Description.Length)	0.408 (0.2958)
	log(Host.Description.Length)ˆ2	−0.0379 (0.0296)
	Host.Gender.FEMALE	−0.2063 (0.0754)***
	Host.Gender.FEMALE + FEMALE	0.7415 (0.4908)
	Host.Gender.MALE + FEMALE	0.039 (0.186)
	Host.Gender.MALE + MALE	−0.3397 (0.3188)
Host-Consumer Interactions	log(Host.Response.Rate)	0.497 (0.6841)
	Host.Response.Time.a few days or more	0.4847 (1.2199)
	Host.Response.Time.within a day	−0.0284 (0.126)
	Host.Response.Time.within a few hours	−0.0139 (0.1002)
	Host.Facebook	−0.3927 (0.0849)***
	Host.Google	−0.0044 (0.1577)
	Host.LinkedIn	−0.3584 (0.4479)
Platform Recommendation	Room.Hot.Room.Icon.recently booked	−1.0977 (0.257)***
	Room.Hot.Room.Icon. frequently booked	1.0076 (0.0814)***
	Room.Hot.Room.Icon.recently viewed	0.2465 (0.108)**
Host Verification	Host.Verified.ID	−0.0798 (0.0958)
	Host.Verified.Personal.Info	−0.0828 (0.0893)
Consumer Ratings	Room.Overall.Rating	6.0042 (2.1837)***
	Room.Overall.Ratingˆ2	−0.6343 (0.2395)***
Control Variables	Room.Type.Entire home/apt	0.8809 (0.4557)*
	Room.Type.Private room	0.6851 (0.4578)
	Room.Accommodates	−0.0976 (0.0221)***
	Room.Normalized.Unit.Price	−0.7904 (0.227)***
	log(Host.Tenure)	3.7382 (2.6324)
	log(Host.Tenure)ˆ2	−0.3643 (0.3334)
	Host.Room.Number	−0.0408 (0.031)

of which enhance consumer purchase behavior (Xie et al., 2017). Higher response rate and faster response speed also strengthen the consumer-supplier relationship, improve trust on supplier, and thus enhance consumer purchase behavior (Gu and Ye, 2014). The supplier-consumer interaction is particularly important in hospitality industry due to the intense service focus and the significant influence of supplier attitude and behavior on consumer perception (Cheng, 2016), which also applies to our Airbnb case. Supplier-consumer interaction is essential when service failure happens, and it can significantly enhance consumer satisfaction and re-purchase behavior (Anderson et al., 2009).

Surprisingly, for most of the cities (except San Francisco and Seattle, in which nonsignificant effect is found), it is found that providing connections to hosts' social media profiles such as Facebook, Google, and LinkedIn negatively correlates with consumers' purchasing decisions. This does not support H3b. Regarding this unusual observation, we conjecture that social media usage is closely related to user personality. People who use social media often typically are more open to express their opinions and sometimes found to be less thoughtful when expressing opinions (Zhong et al., 2011), which might result in the perception of unreliability and decrease consumer purchase behavior. Consumers may perceive that hosts who connect sharing economy accommodation offering and social media are emotional, and thus care less of using accommodation offering as income source, which takes accommodation offering less seriously (Wang and Nicolau, 2017). In addition, people who frequently use social medias tend to spend more time surfing the internet without targeted purposes and are more engaged in multi-tasks (Zhong et al., 2011), which could result in the perception of less caring as hosts, and thus negatively impact consumer purchase behavior.

5.2.4. The impact of platform recommendation on consumer purchase behavior

It is found that for all the eight cities, platform recommendations positively influence consumers' purchase behavior, which supports H4. This shows consumers trust the accommodation-sharing platform, and view the recommendation provided by the platform based on past consumers' webpage view and online booking behavior credible. The recommendation from the platform can serve as a certification offered by the third-party, which is considered as a reliable information source in consumers' eyes (Zhang et al., 2010). This recommendation can be viewed as a comprehensive positive evaluation for both the hosts and their offered products and services from the platform, and thus generates consumer purchase behavior.

Table 2e
Regression results – New York, NY.

Factors Category	Variables	Estimate (Std. Error)
	(Intercept)	−17.3015 (3.1541)***
Product Information	log(Room.Description.Length)	0.1903 (0.2804)
	log(Room.Description.Length)ˆ2	0 (0.0206)
	Room.Number.Photos	0.0283 (0.008)***
	Room.Number.Photosˆ2	−0.0004 (0.0002) **
Host Information	Host.Number.Photos	−0.046 (0.0577)
	Host.Number.Photosˆ2	0.0051 (0.0097)
	log(Host.Description.Length)	−0.0832 (0.1249)
	log(Host.Description.Length)ˆ2	0.0077 (0.0131)
	Host.Gender.FEMALE	−0.0334 (0.0358)
	Host.Gender.FEMALE + FEMALE	−0.1311 (0.1571)
	Host.Gender.MALE + FEMALE	0.1577 (0.1164)
	Host.Gender.MALE + MALE	0.2915 (0.1826)
Host-Consumer Interactions	log(Host.Response.Rate)	−0.0207 (0.2398)
	Host.Response.Time.a few days or more	−0.7601 (0.3894) *
	Host.Response.Time.within a day	−0.2246 (0.0685) ***
	Host.Response.Time.within a few hours	−0.1087 (0.0415) ***
	Host.Facebook	−0.0659 (0.0461)
	Host.Google	−0.1391 (0.0776) *
	Host.LinkedIn	−0.137 (0.1135)
Platform Recommendation	Room.Hot.Room.Icon.recently booked	0.5823 (0.5749)
	Room.Hot.Room.Icon. frequently viewed	−0.4289 (0.1777) **
	Room.Hot.Room.Icon. frequently booked	0.9038 (0.0482) ***
	Room.Hot.Room.Icon.recently viewed	0.1157 (0.0659)*
Host Verification	Host.Verified.ID	0.09 (0.0416)**
	Host.Verified.Personal.Info	−0.067 (0.0452)
Consumer Ratings	Room.Overall.Rating	4.9611 (0.7169) ***
	Room.Overall.Ratingˆ2	−0.5579 (0.0798) ***
Control Variables	Room.Type.Entire home/apt	0.1153 (0.1572)
	Room.Type.Private room	0.0333 (0.1543)
	Room.Accommodates	−0.0433 (0.0112) ***
	Room.Normalized.Unit.Price	−0.3919 (0.109) ***
	log(Host.Tenure)	3.5755 (1.1572) ***
	log(Host.Tenure)ˆ2	−0.3712 (0.1453) **
	Host.Room.Number	0.0137 (0.0293)

Table 2f
Regression results – San Francisco, CA

Factors Category	Variables	Estimate (Std. Error)
	(Intercept)	−10.9514 (5.2056)**
Product Information	log(Room.Description.Length)	0.7757 (0.4335)*
	log(Room.Description.Length)ˆ2	−0.0753 (0.0313) **
	Room.Number.Photos	0.0419 (0.0113) ***
	Room.Number.Photosˆ2	−0.0008 (0.0002) ***
Host Information	Host.Number.Photos	0.005 (0.2538)
	Host.Number.Photosˆ2	0.0021 (0.0678)
	log(Host.Description.Length)	0.0833 (0.1876)
	log(Host.Description.Length)ˆ2	−0.0118 (0.0188)
	Host.Gender.FEMALE	0.0133 (0.0613)
	Host.Gender.FEMALE + FEMALE	0.4114 (0.1791) **
	Host.Gender.MALE + FEMALE	0.0742 (0.1322)
	Host.Gender.MALE + MALE	0.2761 (0.2086)
Host-Consumer Interactions	log(Host.Response.Rate)	−0.3951 (0.4545)
	Host.Response.Time.a few days or more	−1.7211 (1.059)
	Host.Response.Time.within a day	−0.3539 (0.1083) ***
	Host.Response.Time.within a few hours	−0.1207 (0.0659) *
	Host.Facebook	−0.0097 (0.0664)
	Host.Google	−0.2645 (0.1719)
	Host.LinkedIn	−0.0259 (0.1714)
Platform Recommendation	Room.Hot.Room.Icon. frequently booked	0.7373 (0.0721) ***
	Room.Hot.Room.Icon.recently viewed	−0.0035 (0.1191)
Host Verification	Host.Verified.ID	0.1756 (0.0766) **
	Host.Verified.Personal.Info	0.1485 (0.0755) **
Consumer Ratings	Room.Overall.Rating	1.4083 (1.2165)
	Room.Overall.Ratingˆ2	−0.1273 (0.1341)
Control Variables	Room.Type.Entire home/apt	0.3772 (0.2902)
	Room.Type.Private room	0.3357 (0.2826)
	Room.Accommodates	−0.0612 (0.022) ***
	Room.Normalized.Unit.Price	−0.5597 (0.1799) ***
	log(Host.Tenure)	5.261 (1.764)***
	log(Host.Tenure)ˆ2	−0.5766 (0.2169) ***
	Host.Room.Number	−0.2172 (0.0508) ***

5.2.5. The impact of host verification on consumer purchase behavior

It is found that for some cities (e.g., New York, San Francisco, Seattle, Washington D.C.) host verification significantly positively influences consumer purchase behavior, and thus our findings support H5. Verification of host information and identity improves consumer trust in the platform, especially on the platform rules and regulations. Such verification mechanisms indicate organized management, ensure safe online transaction environment, and thus enhance consumer positive perception on the platform's competence, integrity, and benevolence, and thus enhance consumer institutional trust and purchase behavior (Rothaermel and Sugiyama, 2001; Lu et al., 2010).

5.2.6. The impact of consumer ratings on consumer purchase behavior

It is found that for some cities (e.g., Chicago, Los Angeles, New Orleans, New York, Washington D.C.), consumer average overall rating influences purchase behavior. The results from the five cities are consistent: average overall rating increases purchase behavior when the rating is less than 4.5, and the influence extent diminishes with higher rating (as captured by the negative coefficient of the square term *Room.*

Table 2g
Regression results – Seattle, WA

Factors Category	Variables	Estimate (Std. Error)
	(Intercept)	−17.1178 (8.3398)**
Product Information	log(Room.Description.Length)	0.5037 (0.4996)
	log(Room.Description.Length)^2	−0.0291 (0.036)
	Room.Number.Photos	0.0335 (0.0159) **
	Room.Number.Photos^2	−0.0003 (0.0004)
Host Information	Host.Number.Photos	0.1569 (0.167)
	Host.Number.Photos^2	−0.0267 (0.0371)
	log(Host.Description.Length)	−0.1972 (0.236)
	log(Host.Description.Length)^2	0.0276 (0.0228)
	Host.Gender.FEMALE	−0.1056 (0.0715)
	Host.Gender.FEMALE + FEMALE	−0.0458 (0.3062)
	Host.Gender.MALE + FEMALE	0.1177 (0.1326)
	Host.Gender.MALE + MALE	0.2515 (0.4145)
Host-Consumer Interactions	log(Host.Response.Rate)	0.0295 (0.3392)
	Host.Response.Time.a few days or more	−0.4358 (0.4081)
	Host.Response.Time.within a day	−0.0666 (0.1257)
	Host.Response.Time.within a few hours	−0.2335 (0.0778) ***
	Host.Facebook	−0.0893 (0.0776)
	Host.Google	−0.2299 (0.1573)
	Host.LinkedIn	−0.2415 (0.271)
Platform Recommendation	Room.Hot.Room.Icon.recently booked	0.3261 (0.3261)
	Room.Hot.Room.Icon. frequently viewed	0.2462 (0.2491)
	Room.Hot.Room.Icon.great value	0.9655 (0.0795) ***
	Room.Hot.Room.Icon.recently viewed	0.0934 (0.1288)
Host Verification	Host.Verified.ID	0.1981 (0.0925) **
	Host.Verified.Personal.Info	0.1243 (0.0914)
Consumer Ratings	Room.Overall.Rating	5.2099 (3.1471)*
	Room.Overall.Rating^2	−0.5437 (0.3366)
Control Variables	Room.Type.Entire home/apt	0.0324 (0.4516)
	Room.Type.Private room	0.0192 (0.452)
	Room.Accommodates	−0.0593 (0.0257) **
	Room.Normalized.Unit.Price	−0.4458 (0.1706) ***
	log(Host.Tenure)	2.128 (1.7107)
	log(Host.Tenure)^2	−0.1953 (0.2116)
	Host.Room.Number	−0.0772 (0.0248) ***

Table 2h
Regression results – Washington, D.C.

Factors Category	Variables	Estimate (Std. Error)
	(Intercept)	−28.7711 (8.8385)***
Product Information	log(Room.Description.Length)	−0.1728 (0.5121)
	log(Room.Description.Length)^2	0.0261 (0.0369)
	Room.Number.Photos	0.0047 (0.015)
	Room.Number.Photos^2	0.0002 (0.0003)
Host Information	Host.Number.Photos	−0.0412 (0.108)
	Host.Number.Photos^2	0.0031 (0.0185)
	log(Host.Description.Length)	0.2714 (0.2368)
	log(Host.Description.Length)^2	−0.0277 (0.0239)
	Host.Gender.FEMALE	−0.1646 (0.0739) **
	Host.Gender.FEMALE + FEMALE	−0.211 (0.272)
	Host.Gender.MALE + FEMALE	0.2339 (0.154)
	Host.Gender.MALE + MALE	0.1619 (0.2359)
Host-Consumer Interactions	log(Host.Response.Rate)	0.222 (0.553)
	Host.Response.Time.a few days or more	0.5869 (0.9531)
	Host.Response.Time.within a day	−0.3217 (0.128) **
	Host.Response.Time.within a few hours	0.0002 (0.0795)
	Host.Facebook	−0.0702 (0.088)
	Host.Google	−0.0093 (0.1375)
	Host.LinkedIn	−0.354 (0.1534) **
Platform Recommendation	Room.Hot.Room.Icon.recently booked	0.6146 (0.2587)**
	Room.Hot.Room.Icon. frequently booked	1.1218 (0.1217) ***
	Room.Hot.Room.Icon.great value	0.8896 (0.0912) ***
	Room.Hot.Room.Icon.recently viewed	0.2483 (0.1168)**
Host Verification	Host.Verified.ID	−0.1391 (0.0848)
	Host.Verified.Personal.Info	−0.1316 (0.0886)
Consumer Ratings	Room.Overall.Rating	10.5798 (3.0865) ***
	Room.Overall.Rating^2	−1.1425 (0.3341) ***
Control Variables	Room.Type.Entire home/apt	−0.1052 (0.3249)
	Room.Type.Private room	−0.176 (0.3269)
	Room.Accommodates	−0.0693 (0.0226) ***
	Room.Normalized.Unit.Price	−0.6455 (0.1875) ***
	log(Host.Tenure)	2.5592 (2.0267)
	log(Host.Tenure)^2	−0.2503 (0.2559)
	Host.Room.Number	−0.0791 (0.0298) ***

Overall.Rating^2); however, it negatively impacts purchase behavior after that. In this way, our results partially, instead of fully, support H6. Consumers' rating shows past consumers' overall evaluation of their consumption experiences, which serves as an electronic word of mouth influencing future consumer purchase behavior (Cantallops and Salvi, 2014). In this study, we find consumer average overall rating positively influences purchase behavior. However, we need to note two issues. First, the marginal incremental effect is diminishing, which follows the law of diminishing marginal utility (Easterlin, 2005). Second, room listings with a perfect average rating (5.0 out of 5.0) usually lack negative comments, which provide useful information to future consumers about the downside of the service. The perfect rating triggers consumers' doubt about the credibility of the online review source (Chatterjee, 2001; Hu et al., 2009). In addition, many consumers prefer to know more details about the dissatisfied attributes of products and services reflected by previous consumer ratings and reviews, and thus have more familiarity toward the accommodation (Ba and Pavlou, 2002). These all form the concave relationship between consumer average overall rating and purchase behavior.

The empirical evidence in our study is from eight cities over U.S. We found the heterogeneity effects exist between these cities, which result in our above six hypotheses either being strongly supported, partially supported, or not supported. In details, hypotheses that are strongly supported include H3a and H4, in which the results from all or the majority of the cities support. For H3a, we found that for all of the cities except New Orleans, hosts' responsiveness positively affects consumer purchase behavior. For H4, we found for all of the eight cities, platform recommendations positively affect consumers' purchase behavior. Hypotheses that are partially supported include H1, H5, and H6, with either four or five cities' data supporting the hypotheses. In details, for H1, the results from four cities including Los Angles, New Orleans, New York, San Francisco support the hypothesis that the amount of room information has a concave relationship with consumer purchase behavior. For H5, the results from four cities including New York, San Francisco, Seattle, Washington D.C. support the hypothesis that host verification significantly and positively affects consumer purchase

Table 3
Summary of findings.

Hypothesis	Findings	Supported Cities[†]
H1: Concave relationship between the amount of product information and consumer purchase behavior	Partially Supported	Los Angles, New Orleans, New York, San Francisco
H2: Concave relationship between the amount of provider social identity information and consumer purchase behavior	Not Supported	Chicago
H3a: Posting responsiveness information enhances consumer purchase behavior.	Strongly Supported	All of the eight cities except New Orleans
H3b: Posting social network presence information enhances consumer purchase behavior.	Not Supported	None
H4: Posting platform's recommendation information enhances consumer purchase behavior.	Strongly Supported	All of the eight cities
H5: Posting provider verification information enhances consumer purchase behavior.	Partially Supported	New York, San Francisco, Seattle, Washington D.C.
H6: Higher consumer ratings enhance consumer purchase behavior.	Partially Supported	Chicago, Los Angeles, New Orleans, New York, Washington D.C.

[†] All eight cities included in this study are Boston, Chicago, Los Angeles, New Orleans, New York, San Francisco, Seattle, and Washington D.C.

behavior. For H6, consumer ratings positively affect consumer purchase behavior as evidenced by the results from the five cities including Chicago, Los Angeles, New Orleans, New York, Washington D.C. Hypotheses that are not supported include H2 and H3b, in which the results from all or the majority of cities do not support. In detail, for H2, we found for all of the cities except Chicago, the relationship between hosts' social identity information, in terms of their self-description text and photos and consumers' purchase behavior is not significant. For H3b, for all of the cities except San Francisco and Seattle, in which a nonsignificant effect is found, we found that offering connections to hosts' social media profiles such as Facebook, Google, and LinkedIn negatively affects consumers' purchasing decisions. Table 3 summarizes the hypotheses that are either strongly supported, partially supported, or not supported.

5.2.7. *Effect of control variables*

With respect to the control variables, it is found that for most of the cities, the normalized unit price per guest negatively influences consumer purchase behavior. Price directly relates to consumers' perceived utility and value and influences their purchase behavior (Kuo et al., 2009). Our finding supports the previous studies (e.g., Ye et al., 2009) about the negative relationship between price and demand.

In addition, for some cities (e.g. Chicago, Los Angeles, New York, San Francisco), it is found that the tenure of provider has a concave relationship positively influencing consumer purchase behavior, and the extent of influence diminishes with the longer tenure (as captured by the negative coefficient of the square term log*(Host.Tenure)^2*). Namely, tenure has a concave relationship with consumer purchase behavior. Longer tenure accumulates the providers' goodwill and reputation and consumers' purchase behavior (Xu et al., 2017a,b). However, the extent of such influence decreases, which is in line with the law of diminishing marginal utility (Easterlin, 2005).

Moreover, we found for some cities (e.g., Chicago, San Francisco, Seattle, Washington D.C.), the number of rooms hosted negatively influences consumer purchase behavior. One possible reason is that hosts with multiple room listings may spend less time taking care of each room, leading to deteriorated service quality. Having more rooms listed can also increase consumers' doubt about the identity of the owners to be the third-party agents listing rooms, and thus cannot meet their expectation of the interactions with hosts.

Further, we found there is no significant relationship between room type and consumer purchase behavior for most of the cities, possibly because difference between room types is partly captured by the unit price per guest. Lastly, significant negative relationship is observed between number of guests accommodated and consumer purchase behavior for most of the cities, indicating that demand decreases as the room size increases.

6. Theoretical and managerial implications

6.1. *Theoretical implications*

This study is based on four theories: market signaling theory (Heil and Robertson, 1991), social exchange theory (Emerson, 1976), transaction cost theory (Hill, 1990), and information process theory (Gao et al., 2012) to examine the influence of information disclosure on consumer purchase behavior in sharing economy. This study confirms and extends these four theories through answering the questions such as which information source, what information, what information quantities, and in what format, do consumer value.

First, in terms of information source, this study applies and supports the market signaling theory (Heil and Robertson, 1991) through finding the information from all sources of stakeholders – providers (i.e., information about room and provider identity), platform (information about provider-consumer interaction, platform recommendation, and provider verification), and consumers (overall ratings) – providing signals for consumers in sharing economy. Consumers view these signals from difference sources as positive indications that the shared accommodations have good quality and value, which generates their purchase behavior.

Second, in terms of what information, this study applies and supports the social exchange theory (Emerson, 1976) and show that consumers care both the economic and social value in building and maintaining the relationship with providers. The cost-benefit analysis is the key in social exchange theory determining consumers' willingness to build and maintain the relationship with sellers (Shiau and Luo, 2012). This study reveals that the cost-benefit analysis is more complex in sharing economy due to the multiple new aspects of costs and benefits. In addition to the economic perspective, social interactions with providers, providers' social identity, rooms' various attributes through description also influence consumers' purchase behavior. Consumers' purchase behavior in sharing economy also depends on their relationship with the platform. The platforms' recommendation and provider verification enhance consumers' trust toward the platform, which also stimulate their purchase behavior.

Although information disclosure can provide positive signals to consumers, reduce perceived risk, increase trust, and thus generate purchase behavior, too much information disclosure brings the opposing effects. In this way, this study applies and supports the transaction cost theory (Hill, 1990) through examining how information and search cost affects consumers' purchase behavior. It is found that too much information disclosure increases consumers' hassle costs to search and acquire the information and increase asset specificity, which negatively influence their purchase intension. In terms of information format, we find that all formats of text, visual, and ratings influences consumers' purchase behavior.

This study also confirms the information process theory and shows that information overloading limits consumers' cognition and prevents perceiving, processing, and responding to efficient information. We apply and support the information process theory (Gao et al., 2012) through identifying the subset of information on which consumers would like to narrowly focus when they face information overloading. We find that in terms of information quantities, the length of room text description and number of photos about room have a concave relationship with consumers' purchase behavior. This shows that although information disclosure encourages consumers' purchase behavior, going beyond the limit is as bad as falling short – too much information would just have the opposing effect.

6.2. Managerial implications

The objective of platform owners is to facilitate the transaction between providers and consumers. This study examines how information disclosure can affect consumers' purchase behavior, which provides implications for the platform to increase consumer demand through better designing the information disclosure mechanism.

The platforms can disclose information through direct and indirect ways. Direct ways include posting the information by platforms themselves. Our study finds that information about provider verification, platform recommendation, and provider-consumer interaction stimulates consumers' purchase behavior. The platform needs to expand the channels to verify providers' information. One of the biggest concerns for consumers to participate in collaborative consumption is the security issue, and lacking regulation is the main concern. Provider verification by the platform through various ways can show the platform's intention to regulate, monitor, and control the providers and transactions, which enhances consumers' perceived transaction security and generate their purchase behavior. In addition to verifying photos and ID, platforms can also verify providers' online accounts, ensure their description about product and themselves is genuine, and implement the verification efforts both online and offline. Platform recommendation is viewed as a credible source for consumers to refer for product evaluation, and thus stimulates the transaction. Platforms can design various programs such as encouraging the providers to join in certification program and publicly display such certification on the platform. Information such as popular rooms, recently-booked rooms, and consumers' favorable rooms can also be released to enhance consumers' purchase behavior. Platform can also encourage more intensive interaction between providers and consumers through awarding providers who always provide rapid responses to consumers' inquiries. One of the ways to award these providers is to provide promotional symbols on the platform showing the platform's recommendation about the fast-response providers. In this way, the provider-consumer-platform relationship will be further strengthened, which enhances consumer purchase behavior.

The platform can also facilitate and regulate the information disclosure in the indirectly way from providers and consumers. Our study finds all sources of information with various formats are valued by consumers to generate their purchase behavior. Thus, encouraging both providers and consumers to post various forms of information such as text description, photos, ratings, and demo videos are helpful for consumers to learn about the products and services through a comprehensive view.

For designing purposes, the platform should consider the contents and quantity the information disclosed. Regarding contents, comprehensively covering all aspects of the product and service attributes can be helpful. Particularly, in addition to the economic value, social value is also acknowledged by sharing economy consumers. Social interaction information such as providers contact, communication, and response should be released. Past performances and experiences about social interaction, and communication channels should also be emphasized. Seeking social interaction with local people such as providers and peer consumers is one of the main motivations for consumers to be involved in sharing economy (Hamari et al., 2016). Thus, the platform should have a better design to encourage interactions. For example, the platform can encourage peer consumers to post comments and be actively involved in online reviews and forums through monetary incentives, adding providers' response to consumers' reviews to provide feedback, and adding more direct communication channels among all parties such as through live online chat. In this way, the platform can serve as an intermediary not only for transaction, but also for social interaction as well.

However, not all information is valued equally by consumers. This is reflected by our findings from two aspects. First, because consumers can only deal with a subset of information due to the limit information process capacity, some information such as auxiliary attributes of products and service disclosed to consumers is ignored by consumers. Extra and unimportant information can even have the negative effect on consumer information search and acquisition due to information overloading issues. Hence, the platform should consider removing the information not valued by consumers when redesigning listing displays. This will avoid the confusion of information acquisition for consumers and amplify the positive effect of other information on consumers' purchase decision. In addition, even for the valuable information, the quantity of information posted needs to be carefully considered. Too much information increases asset specificity and the associated information and search costs for consumers, which negatively influences consumers' purchase behavior. We find both the room description by words and number of photos of rooms have a concave relationship with consumers' purchase behavior, which shows the information value consumers acknowledge, but too much information is as bad as too little. The platform should limit the number of words or characters for the room description and set an upper limit for the number of photos for the room. Knowing the excess information is just as bad as deficiency, the platform can reduce the transaction cost for consumers and enhance their purchase behavior.

7. Conclusions and extensions

With the background of rapid development of information technology, platform economy, and consumers' adoption of sharing economy, this study examines the role of information disclosure in influencing consumers' purchase behavior in sharing economy. This study analyzes information disclosure from four aspects – namely, what information (i. e., information content), from where (i.e., information source), in what format (information presentation format), and how much (the quantity of information). We aim to find whether the above four aspects of information influence consumers' purchase behavior in sharing economy, if yes, what is the mechanism of such influence?

Via the empirical evidence from Airbnb accommodation-sharing platform and the data collected from eight major cities in U.S., we examined three aspects of the information sources posted from providers, the platform, and peer consumers. We find that all three information sources influence consumer purchase behavior. In detail, regarding the providers' self-presentation information, we find a concave relationship between the products (i.e., rooms) and consumer purchase behavior. Namely, the number of photos and the length of room description positively influence consumer purchase behavior, and such influence diminishes with additional photos and text description. However, no significant relationship between providers' self-description identity in terms of texts and photos and consumer purchase behavior is found.

Regarding information posted by the platform, we find that the recommendation from the platform and provider verification information posted by the platform positively influence consumer purchase behavior. For provider-consumer interactions information, we find that providers' responsiveness, which is reflected by high response rate and fast response speed, enhances consumer purchase behavior. However, providing connections to providers' social media profiles such as

Facebook, Google, and LinkedIn negatively influences consumers' purchasing behavior.

Regarding the information from peer consumers, we find a concave relationship between consumers' overall rating and consumer purchase behavior. Namely, the perfect score posted by consumers may not necessarily have the most significant positive influence on consumer purchase behavior. Although consumers' overall ratings positively influence consumer purchase behavior, such influence diminishes when the ratings exceed a certain threshold.

Our study provides implications for platform owners to stimulate consumers' purchase behavior through optimizing information presentation directly through the platform design or indirectly through the guidance on providers' information disclosure. Better platform design can facilitate consumers to reduce their information and search cost and enhance their effectiveness of information processing. Consumers can learn more about the products, services, providers, and the platform to reduce the perceived risk, enhance trust between the providers and the platform, and thus enhance consumer purchase intention and behavior.

Our study has several limitations, which open the directions for future research. First, our study examines the consumer purchase behavior in sharing economy through the empirical evidence from the eight cities in U.S. Some results reflect heterogeneity across the various cities. Future studies can explore in more depth about how regional characteristics such as culture and environment affect consumer purchase behavior in sharing economy. Second, one of the information sources examined in this study is from peer consumers. We analyzed the role of consumer ratings in affecting future consumers' purchase behavior. Future studies can also focus on the textual comments of consumers through text mining techniques and explore the impact of the contents of these comments on consumers' purchase behavior. In addition, future studies can investigate the influence of contents of providers' responses on consumers' purchase behavior. Last, in this study, although we discuss the impact of hosts' social information on consumers' purchase behavior in sharing economy, we did not consider the potential differences of the security preference of personal social information among the providers. It is possible that not all providers are willing to disclose their own information. Therefore, future studies can analyze the influence of the providers' security preference of personal social information and their personality on consumers' purchase behavior.

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