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How does constraining description affect guest booking decisions and satisfaction?

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ABSTRACT

The importance of hosts' information disclosure on influencing guest behavior and matching efficiency has been proven by many studies. Most peer-to-peer rental platforms allow hosts to disclose constraining descriptions (such as house rules) to regulate guest behaviors. However, the effects of this specific type of information disclosure on subsequent guest behaviors and host performance remain unclear. Thus, based on a unique longitudinal dataset collected from Airbnb, this study investigates how constraining descriptions influence the booking decisions and satisfaction of subsequent guests. Results show that constraining descriptions related to topics, including civilization-related, living conditions, personal activities, and host management boost the review volume but decrease guest satisfaction and cause rating loss. Degree of competition, hosts' prior reputation, and price moderate the relationship between constraining descriptions and subsequent guest behaviors. As an early attempt to focus on the consequence of hosts' constraining descriptions, this study contributes to tourism literature and property hosts in practice.

1. Introduction

Peer-to-peer rental platforms (e.g., Airbnb and Xiaozhu platforms) have become a popular trend in recent years because of their strong social and economic attractiveness (Pizam, 2014; Tussyadiah, 2016). However, some studies have indicated that the main barrier to sustainable development for such platforms is the lack of trust (Scerri & Presbury, 2020; Xie & Mao, 2017). Compared with traditional accommodation platforms, such as hotel booking platforms and peer-to-peer rental platforms offer products and services with high heterogeneity, which requires guests to search for more information to differentiate host quality (Liang, Schuckert, Law, & Chen, 2017). Although user-generated content, such as online reviews, has been proven to be an effective information source on hotel booking platforms, prior studies have noted its limitations on peer-to-peer rental platforms. For example, the limited capacity of properties in peer-to-peer rental platforms has resulted in a relatively scant number of reviews compared with hotel booking platforms (Liang, Schuckert, Law, & Chen, 2020). Some studies have also indicated the existence of review or rating bias on peer-to-peer rental platforms, such as Airbnb (Holtz & Fradkin, 2020; Pera, Viglia, Grazzini, & Dalli, 2019). Zervas, Proserpio, and Byers (2021) compared the rating distribution between Airbnb properties and TripAdvisor hotels and found that the ratings in Airbnb are relatively much higher and have lower variations than those in TripAdvisor. Thus, the high demand for information search and the limited supply of user-generated content lead to more prominent information asymmetry on peer-to-peer rental platforms (Gong, Liu, Liu, & Ren, 2020; Yan & Zhao, 2011; Yao, Qiu, Fan, Liu, & Buhalis, 2019).

Most peer-to-peer rental platforms require and encourage their users (mostly hosts) to disclose information on their properties and themselves to provide more credible information sources that can help guests differentiate between the quality of their properties and the hosts themselves. The disclosed information includes two parts. One part requires hosts and guests to upload their identification information, such as government-issued ID, email address, and phone number, to the platforms. Such information is private, and platforms will assign badges after users have uploaded the corresponding information. Liang, Li, Liu, and Schuckert (2019) investigated the motivations behind the

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information disclosure behaviors of hosts in Airbnb and found that high volume, valence, and quality of guest reviews can significantly motivate hosts to disclose more information subsequently. The other part of disclosed information is the textual and graphic descriptions of properties and hosts that have attracted relatively more academic attention. Liang et al. (2020) found that providing detailed textual descriptions of the properties and hosts can boost subsequent review quantity and ratings. Zhang, Lee, Singh, and Srinivasan (2021) noted that Airbnb properties with verified photos have 17.51% more demand and can generate additional revenues of $2521 per year compared with properties without photos. Recent studies have also observed the effects of hosts' selfies on guest behavior. For example, Peng, Cui, Chung, and Zheng (2020) found that hosts with beautiful and ugly profile pictures generate more revenues than plain-looking hosts.

In summary, many prior studies have begun to verify the importance of hosts' information disclosure. However, very few have looked further into the mechanisms behind the effects of hosts' information disclosure on the booking intentions of guests and how property hosts disclose information more effectively. Concerning the textual descriptions of properties, traditional textual descriptions of products and services include two parts: introduction of objective attributes and promotion information (Chandrasekaran, Annamalai, & De, 2019). As a two-sided platform, peer-to-peer rental platforms allow hosts to present or disclose another type of information, namely, constraining description (such as house rules on Airbnb). This information can help guests understand the preferences and personalities of property hosts while enabling the latter to regulate guest behavior by announcing the house rules in advance (Scerri & Presbury, 2020). On Airbnb and similar platforms, property hosts can present their house rules, and all guests will be informed if they try to book the corresponding properties. As a new type of information, the consequences of providing constraining descriptions have not been explored in prior studies. First, if hosts present strict house rules, some leisure guests may perceive that their freedom will be restricted, and thus, divert their attention to other properties. Second, according to the persuasion knowledge model, consumers or guests are more likely to identify positive statements from sellers as persuasive information and perceive high deception (Scerri & Presbury, 2020). From this perspective, property descriptions, including house rules (a statement of prohibited items) are easier to perceive as credible. In summary, how the constraining description disclosed by hosts influences the booking decisions and satisfaction of subsequent guests and in turn affects host performance is still unclear. To this end, this study intends to investigate the effects of the constraining description disclosed by hosts on subsequent guest booking decisions and satisfaction by constructing a conceptual framework and collecting a unique longitudinal dataset from Airbnb. The detailed research purpose of this study is threefold: (1) to analyze the detailed topics of constraining descriptions based on text mining approaches, (2) to explore the effects of constraining descriptions on subsequent guest booking decisions and satisfaction on peer-to-peer rental platforms, and (3) to observe whether the above relationship is moderated by the competitive intensity and host's prior reputation.

2. Literature review

Information disclosure has long been an important research issue in corporate management. Prior literature regarding information disclosure covers two types of information: company-oriented and product- or service-oriented information. For company-oriented information disclosure, most studies focused on the strategic management of the company and included the motivation of information disclosure and its outcomes. For example, researchers found a positive correlation with corporate efficiency when the transparency of corporate environmental, social, and governance information is at a medium level of disclosure rather than a high or low level (Xie, Nozawa, Yagi, Fujii, & Managi, 2019). As for traditional product- or service-oriented information disclosure, the reason for the disclosure is to give additional information to the consumers and try to provide personalized customized products or services. Many existing studies have shown that effective information disclosure can promote consumer purchase intention and repeat purchase behavior, which will have a positive effect on guest booking intentions. For example, researchers found that in the platform operation of leasing services, product information disclosure supported by blockchain technology is crucial to attracting customers (Choi, Feng, & Li, 2020).

Concerning sharing economy platforms, service providers are always required and encouraged to disclose information related to their properties and services and information on themselves to help guests infer the service quality and improve trust (Liang, Schuckert, Law, & Chen, 2017; Xie & Mao, 2017). Some studies have also indicated the effectiveness of various types of the disclosed information on the improvement of guest booking decisions, satisfaction, and host performance. For example, based on rational choice and utility maximization theories, Liang et al. (2020) found that the width and depth of the property and host's textual descriptions can significantly boost subsequent review volumes of corresponding properties. By contrast, most prior studies focused on verifying the effectiveness of host-oriented information, including host's textual descriptions (Garcia, Munoz-Gallego, Viglia, & Gonzalez-Benito, 2020; Zhang, Yan, & Zhang, 2020) and profile photos (Barnes & Kirshner, 2021; Ert, Fleischer, & Magen, 2016; Fagerstrom, Pawar, Sigurdsson, Foxall, & Yani-de-Soriano, 2017). Garcia et al. (2020) investigated the correlation between hosts' self-presentation and Airbnb listing performance and found that the self-presentation strategy showing social values leads to higher revenues while the strategy that emphasizes hosts' interests has a negative effect. Zhang, Yan, and Zhang (2020) found that the readability of host self-description can positively affect consumer purchase behavior by improving the sense of trust for consumers. They also found that a different emphasis in the description will have different effects, with information related to family relationships, openness, service, and travel experience benefitting from the building of trust. In addition to textual information, some studies also focused on the effects of photo information. For example, Ert et al. (2016) investigated the importance of host photos and found that the reliability shown in photos positively affects consumer purchase behavior. Jaeger, Sleegers, Evans, Stel, and Van Beest (2019) found that hosts with smiling faces attract more customers than those with non-smiling faces, and black face hosts have lower performance than Asian face hosts.

Although recent researchers have studied the outcomes and consequences of information disclosure for the sharing economy, most still focus on demonstrating the importance of information disclosure. Fewer researchers have studied the mechanism behind the effects of host information disclosure on guest behavior and how to provide information to better improve host performance and matching efficiency. Most prior studies have focused on one function of disclosed information, such as the introduction of product or service characteristics or promoted information. In this study, however, we focused on another type of host description on peer-to-peer property rental platforms, namely, constraining description, to regulate guest behaviors. The relevant concept in tourism literature is travel constraints, which originated from the leisure literature (Gao & Kerstetter, 2016; Hung & Petrick, 2012). Crawford, Jackson, and Godbey (1991) first constructed the conceptual framework for constraints in the context of leisure and classified this definition into three dimensions: intrapersonal, interpersonal, and structural constraints. Intrapersonal constraints refer to constraints and inhibitors for psychological conditions of individuals, such as their preferences, while interpersonal constraints represent the inhibitors for individuals to interact with others. Finally, structural constraints include external factors restraining travelers' behavior intentions such as time or financial resources (Chen & Petrick, 2016).

In peer-to-peer property rental platforms such as Airbnb, each property host must transfer the right of use of their properties to strangers. Thus, in addition to disclosing information to introduce details on their properties and themselves, property hosts also have demands to present another kind of description (such as house rules in Airbnb), namely constraining description to regulate guest behavior and protect property security. Based on the particularities of peer-to-peer rental platforms, our research purpose is to investigate the effect of this special type of host description on guest booking decisions and satisfaction. Thus, according to our research purpose and the conceptual framework presented by Crawford et al. (1991), we defined constraining description as descriptive contents generated by service providers and its purpose is to provide structural constraint to regular guests' unethical behavior (Scerri & Presbury, 2020). To the best of our knowledge, none of the prior studies have focused on the effect of this specific disclosed information on subsequent guest behavior and host performance. Thus, to fill this research gap, the present study will focus mainly on the effects of the disclosure of constraining descriptions on guest booking decisions and satisfaction and attempt to compensate for the deficiencies of existing information disclosure-related research.

3. Hypothesis development

3.1. Constraining description and guest booking decisions

Consumers may have a higher perceived risk of the products and services in peer-to-peer rental platforms because of the strong information asymmetry between the guests and hosts of the platforms; such asymmetry has a negative effect on consumers' purchase intentions and behaviors (Xie & Mao, 2017). Researchers have found that obtaining more information can improve consumers' perception of the quality of products and services, which indicate the fairness of prices, thereby improving consumers' perception of fairness and guest booking intentions (Caldieraro, Zhang, Cunha, & Shulman, 2018). Therefore, the volume of information disclosed by service providers has become an important factor affecting guest booking decisions in peer-to-peer rental platforms. Some recent studies have found that Airbnb guests are more likely to book properties with more sufficient disclosed information (Xu, Zeng, & He, 2021). However, very few studies have focused on the effects of constraining descriptions disclosed by hosts. As an important part of hosts' disclosed information, constraining description can also disclose information related to properties and hosts to potential guests. Thus, such information can also help guests gain more understanding of the properties and hosts, which can reduce the uncertainty of their choices (Liang et al., 2019). From this perspective, guests should focus more attention to properties with more disclosed constraining descriptions.

Prior studies have also found that in traditional accommodation booking platforms, user-generated content, such as online reviews, has a greater influence on consumer purchasing behavior than marketer-generated content (Goh, Heng, & Lin, 2013). The main reason is that, based on the persuasion knowledge model, marketer-generated content, especially those that contain positive emotions, is more likely to be regarded as persuasive information, which is perceived by consumers as being less credible (Isaac & Grayson, 2017; Zhang, Yan, & Zhang, 2020). By contrast, constraining descriptions in peer-to-peer rental platforms, such as house rules, seeks to present constraints to regulate guest behavior. By consulting such information, guests can gain more understanding of the host's preferences and personality. Moreover, as a type of information containing negative emotions, constraining description is likely to be perceived as being more credible. In summary, we expect properties with more detailed constraining descriptions to be more likely to attract guests to book properties and post reviews. From this aspect, the following hypothesis is put forward.

H1a. The content information richness of constraining descriptions (house rules) has a positive effect on guests' booking and review posting decisions.

Prior studies have also reported that most guests in peer-to-peer rental platforms book properties for leisure purposes (Gibbs, Guttentag, Gretzel, Yao, & Morton, 2018; Sainaghi & Baggio, 2020), and one of the most important factors that influence the traveling decision of leisure tourists is perceived freedom (Agyar, 2014; Lapa, 2013). The concept of perceived freedom is defined as a state in which the person feels that what they are doing is by choice and because they want to do it; in other words, it is a sense of freedom formed by the subjective will of the individual without any hindrance or coercion (Ellis & Witt, 1984; Siegenthaler & O'Dell, 2000). Prior studies have found that the sense of freedom perceived by consumers will lead to a positive attitude and behavior (Agyar, 2014). However, the purpose of constraining descriptions, such as house rules, is to regulate guest behavior at a specific time and place (Lau & Wenzel, 2015). Accordingly, although constraining description is a specific type of information source, it can help guests differentiate the quality of properties and hosts. For instance, some guests will perceive less freedom when booking properties with strict constraining descriptions. From this perspective, the guest will be less likely to book properties with more constraining descriptions.

H1b. The content information richness of constraining descriptions (house rules) has a negative effect on guests' booking and review posting decisions.

3.2. Constraining description and guest satisfaction

The content richness of constraining descriptions is expected to be negatively associated with guest satisfaction. Prior studies focusing on the determinants of consumer satisfaction have mostly shown that consumer satisfaction is decided by expectations before consumption and perceived performance after consumption (Narangajavana Kaosiri, Callarisa Fiol, Moliner Tena, Rodriguez Artola, & Sanchez Garcia, 2019). More detailed constraining descriptions can help guests gain more understanding of the restrictions of properties and hosts. Therefore, they can better adjust their expectations according to their preferences, which may improve their satisfaction after consumption. For example, when hosts list "No Smoking" in their house rules, guests who prefer to smoke in the room can adjust their exceptions in advance. Thus, their satisfaction may not be affected because smoking is prohibited.

However, detailed constraining descriptions may further improve guests' expectations for two reasons. First, based on rational choice theory, customers will only choose if the expected benefits outweigh the costs (Becker, 1968). If the properties disclosed more detailed constraining descriptions, guests would have to exert more searching costs to weigh the advantages and disadvantages of their booking decisions. Thus, based on rational choice theory, guests who have booked properties with detailed constraining descriptions have high expected benefits and expectations before consumption, which may hurt their satisfaction after consumption (Hu & Krishen, 2019; Lurie, 2004; Messner & Wanke, 2011). Second, many studies have proven the persuasive effect of information, including user-generated and marketer-generated content (Colicev, Kumar, & O'Connor, 2019; Goh et al., 2013). Information containing positive emotions, such as positive online reviews, can improve the purchasing intention of consumers, whereas information containing negative emotions may have the opposite effect (Zhao, Wang, Guo, & Law, 2015). Therefore, most marketer-generated content in traditional online travel agencies and social media platforms seldom disclose negative information, though many consumers are suspicious of its credibility (Meire, Hewett, Ballings, Kumar, & Van, 2019). The particularity of peer-to-peer rental platforms requires hosts to disclose constraining descriptions to regulate guest behavior and protect the safety of transactions. According to signal theory, consumers tend to identify different signals based on different information sources to help them infer the quality of products or services (Riasi, Schwartz, & Chen, 2018). As noted above, constraining descriptions may present negative signals for some leisure travelers because of the limitations to their freedoms. However, given the existence of this potential negative signal, guests who have booked such properties should discover other positive signals related to service quality. For example, although detailed constraining descriptions have resulted in some restrictions to guests' freedom, the guests may perceive the hosts as having high expertise related to information disclosure and user management, which could further increase their expectations.

Finally, theories in the fields of information economics suggest that more complete symmetric information improves the efficiency of market equilibrium (e.g., Kanodia, 1980). However, for peer-to-peer rental platforms, many studies have noted that the use of a bilateral review system causes a positive bias of review score rating (Holtz & Fradkin, 2020; Pera et al., 2019; Zervas et al., 2021), which will obscure real market information and lead to market imbalance. Accordingly, providing more information from other perspectives (such as constraining descriptions generated by listing owners) about a product may have a negative effect on guest satisfaction and review ratings by unveiling the true equilibrium. Thus, the following hypothesis is put forward accordingly.

H2. The content information richness of house rules has a negative effect on the satisfaction of shared accommodation guests.

3.3. Moderating effect of external competition intensity

Consumers have more choices and more initiative when external competition intensity is high, and a large amount of alternative listing information increases the costs of consumers' information search. In this case, information overload is prone to occur, resulting in low purchase intention (Krishen, Raschke, & Kachroo, 2011). Guests' limited attention may also push them to focus more on direct cues related to price or service quality to better reduce their uncertainties (Zhang, Liang, Li, & Zhang, 2019). By contrast, if competition intensity in peer-to-peer rental platforms is relatively low because of the limited choices, then consumers will have enough time to read and screen the information provided by the listings. In this context, the constraining descriptions represented by the house rules can be disclosed effectively to consumers to enable them to obtain more useful information, thereby reducing information asymmetry and uncertainty of choice and improving consumers' purchase intention (Zhu, Mou, & Benyoucef, 2019). Therefore, the present study assumes that the degree of external competition for listings will negatively regulate the main effects of house rules disclosure on guest booking decisions. Accordingly, we present the following hypothesis:

H3a. The effects of house rules disclosure on guests' booking decisions are weakened when the degree of external competition intensity for listings is high.

For guest satisfaction, in the case of fierce external competition, as noted above, customers can choose from many alternative listings, and thus, they are more likely to choose satisfactory properties through rigorous analysis and comparison. For properties with detailed house rules, although guests spend additional searching costs to infer the service quality of properties, such information can effectively help them find satisfactory choices according to their preferences. Meanwhile, according to endowment effect theory, when guests spend more when choosing in a fierce external competition environment, they tend to have a higher evaluation of their choices after consumption (Bao & Gong, 2016; Weaver & Frederick, 2012). In this case, if the guest has already decided and comes to live in the listing they have chosen from many alternatives with high searching costs, they will then convince themselves to believe that their choice is right. Therefore, this study assumes that when the external competition of listings in peer-to-peer rental platforms is relatively high, the effects of house rules disclosure on guests' satisfaction are amplified to some extent. Hence, the following hypothesis is proposed:

H3b. The negative effects of house rules disclosure on guests' satisfaction are weakened when the degree of external competition intensity for listings is high.

3.4. Moderating effect of host reputation

In addition to the intensity of the external competitive environment, many studies have indicated that the personal reputation of hosts on the platforms will also influence guest booking decisions and satisfaction. In Airbnb, platform managers identify hosts with a high reputation (completed at least 10 itineraries or 3 reservations, and the total number of nights of accommodation has reached 100 nights; response rate is not less than 90%; cancellation rate is not higher than 1%, and the overall score is maintained at 4.8) on the platform as a "Superhost" and assign virtual badges to announce their reputation to all platform users (Liang, Schuckert, Law, & Chen, 2017; Gunter, 2018). Thus, the "Superhost" badge serves as a positive cue related to service quality. Prior studies have noted that guests are willing to pay a premium for listings belonging to a "Superhost" (Liang, Schuckert, Law, & Chen, 2017). Detailed information on house rules is also a positive cue of credibility for guests (Ert & Fleischer, 2019). In this case, these consistent cues enhance the positive effect on guests' booking decisions (Brucks, Zeithaml, & Naylor, 2000). Meanwhile, constraining descriptions presented by house rules may cause guests to feel restricted, thereby sending a negative signal for the guests' purchase (Siegenthaler & O'Dell, 2000). Hence, for those guests, the cues related to constraining descriptions disclosed by hosts and "Superhost" cues are two inconsistent cues that may lead to cognitive dissonance. Accordingly, the perceived credibility of constraining descriptions will be reduced because of the inconsistent cues, and thus, the negative effects of constraining descriptions disclosed by hosts on guest booking decisions and purchasing intentions would also be weakened. Hence, we present the following hypotheses.

H4a. The positive effects of house rules disclosure on guests' booking decisions are enhanced when the host has a "Superhost" badge.

H4b. The negative effects of house rules disclosure on guests' booking decisions are weakened when the host has a "Superhost" badge.

For guest satisfaction, even if disclosing more detailed constraining descriptions will lead to low satisfaction by increasing the guests' expectations, this negative effect can be weakened if the perceived performance of guests after the living experience is increased and is closer to their expectations (Liang, Schuckert, & Law, 2017). When one host has a "Superhost" badge, it means their service quality has been identified by prior guests and platform managers (Gunter, 2018). Thus, guests who booked properties belonging to the "Superhost" will more likely have high perceived performance after consumption. For these guests, the negative effect of constraining descriptions disclosed by hosts on their satisfaction will be weakened. Thus, we propose the following hypothesis:

H4c. The negative effects of house rules disclosure on guests' satisfaction are weakened when the host has a "Superhost" badge.

3.5. Moderating effect of price

Price is an important factor that affects guest purchase booking decisions and satisfaction. Thus, we also analyzed the moderating effects of price on the relationship between constraining description and guest booking decisions and satisfaction. On the one hand, according to previous research, one of the reasons for consumers to choose shared accommodations is its relatively lower price as compared with hotels (Guttentag, Smith, Potwarka, & Havitz, 2018; So, Oh, & Min, 2018). Thus, guests in Airbnb are more likely to be sensitive to price and costs. Although the constraining description provides an effective information source for guests to gain more understanding of the properties and hosts, additional searching costs may be required of the guests to acquire such information. Thus, when guests intend to book a high-priced property, such additional searching costs brought by reading constraining information may reduce their intention to make booking decisions. Accordingly, guests who booked high-priced properties will be more sensitive to the additional searching costs, which would weaken the positive effect of constraining description on booking decisions.

On the other hand, based on the rational choice theory, guests who book high-price listings should have relatively high expected benefits and expectations because of the high costs. It causes guests to further confirm the increased expectations brought by detailed constraining descriptions. In addition, if guests are not satisfied with the product or service quality of high-priced listings that disclosed detailed constraining descriptions, then they will perceive that they have encountered not an only economic loss but also restrictions to freedom, which will further hurt their satisfaction after consumption. Hence, we propose the following hypothesis:

H5a. The positive effects of house rules disclosure on guests' booking decisions are weakened when the price of listings is high.

H5b. The negative effects of house rules disclosure on guests' satisfaction are amplified when the price of listings is high.

The conceptual framework is presented in Fig. 1.

4. Methodology

4.1. Data collection

The data used in this study were collected from the Airbnb (www.airbnb.com) platform. As one of the biggest peer-to-peer rental platforms worldwide, Airbnb has attracted considerable academic attention (Hardy, Dolnicar, & Vorobjovas-Pinta, 2021; Leoni, 2020; Volgger, Taplin, & Pforr, 2019). Moreover, as a kind of two-sided platform, Airbnb allows all listing owners to disclose textual descriptions and regulate guest behaviors. It requires listing owners to disclose house rules to help guests understand the restrictions during the living process. Airbnb hosts can also freely adjust and update all textual descriptions and house rules according to their prior matching efficiencies, which provides us with a unique context to study the dynamic changes in constraining descriptions (house rules) on subsequent guest decisions and satisfaction of guests. Accordingly, this study developed a crawler program written in Python to dynamically collect the contents of house rules and other characteristics related to listings and hosts (e.g., room types, number of beds, price, and level of competition) of all listings in New York City, Los Angeles, Chicago, and Austin from January 2019 to June 2020. At the same time, the IDs of each listing and host were collected as a unique identification symbol. The final dataset is a monthly longitudinal dataset covering 90,332 listings in New York City, 80,322 listings in Los Angeles, 15,919 listings in Chicago, and 19,884 listings in Austin or a total of 206,457 listings in all cities.

4.2. Variables

Our dependent variables include the number of bookings and guest satisfaction. Many studies have indicated that the number of bookings is highly related to the review volume of the listings (Xu, 2020; Xu et al., 2021; Zhang, Zhang, Law, & Liang, 2021). Because Airbnb only allows guests who have booked the listings to post reviews, more reviews in a listing means it has attracted more bookings in the past. Many prior studies have also used review volume as proxy for guests' booking decisions (e.g., Liang et al., 2020). Thus, we used review volume as proxy for guests' booking decision (*Review_num*). Moreover, to be consistent with prior studies (e.g., Li & Ryan, 2020; Zhang, Qiao, Yang, & Zhang, 2020), we used the guests' overall ratings as proxy for their satisfaction (*Review_score*). Concerning constraining descriptions, we used information posted by hosts pertaining to "house rules" to represent constraining descriptions. The purpose of hosts in posting constraining descriptions is to regulate guest behavior. Thus, Airbnb sets a single description item (house rule) to attract guests' attention and remind the guests on the house rule information again before they finally finish payment for the bookings. Accordingly, we assume it is less possible for hosts to tend to post content related to constraining descriptions on other items of textual descriptions together with other types of information. This study uses the number of topics (*Topic_num*) in each house rule to represent the content richness of constraining descriptions and verify the relevant hypotheses.

This study also selected the degree of competition intensity, host reputation, and price as moderating variables to explore whether the effects of the richness of the content of constraining descriptions will change under different conditions. The degree of competition intensity is measured by the number of listings in the same zip code area while host reputation is measured by the dummy variable of whether the host has a "Superhost" badge. Price is measured by the nightly rate of each property. Finally, to ensure accuracy of the empirical results and the completeness of the model, this study introduced a series of control variables related to the characteristics of listings, including text length of listing description, room type, maximum guest capacity, number of amenities in the room, number of beds, and degree of cancellation policies. The three other control variables are related to the characteristics of the hosts: whether the hosts posted their selfies, the number of listings managed by the host, and whether the host is local (whether the city where the listing is located is the same as the homeowner location of listing owners). Finally, because our study period is from January 2019 to June 2020, which included the COVID-19 pandemic period, we also controlled for the new COVID-19 cases each month by zip code to remove the possible influence caused by a COVID-19 event. All related variables are described in Table 1.

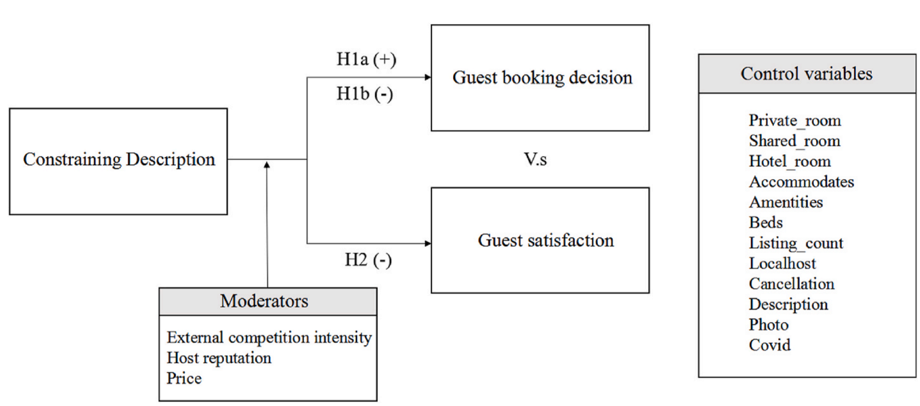

Fig. 1. Conceptual framework.

Table 1
Description of correlation variables.

Variables	Description
Dependent variables	
Review_num	Number of reviews of each property
Review_score	Overall rating of each property
Independent variable	
If_have_houserules	Whether or not the host disclosed house rules
Topic_num	Number of topics of the constraining description
Competition	Degree of competition, which is measured by the number of shared accommodation listings in the same zip code area
Superhost	Whether the current host has the "Superhost" badge
Control variables	
Private_room	Whether or not the property is a private room
Shared_room	Whether or not the property is a shared room
Hotel_room	Whether or not the property is a hotel room
Accommodates	Maximum guest capacity
Amenities	Number of amenities in each property
Beds	Number of beds in each property
Price	Average daily room rate of each property
Listing_count	Number of listings managed by the same host
Localhost	Whether or not the listing located city is the same as the hometowner location of listing owners
Cancellation	The strict degree of cancellation policies, varying from 1 (flexible) to 3 (strict)
Description	Text length of the listings' descriptions about the property
Photo	Whether or not hosts upload their profile photos
Covid	New Covid-19 cases of each neighborhood

4.3. Empirical models

To choose a proper model for this study, we first conducted the joint significance test of individual effect and a random effect for all our following models to choose a proper model for this study. The results showed that panel analysis is necessary ($p = 0.000$). We then performed the modified Hausman test to choose whether to use a fixed effect model or a random effect model. The result showed that the model with fixed effect is more appropriate for this study ($p = 0.000$). In addition, the dummy variables of each month were jointly significant for all model types below. Therefore, in this study, we constructed two-way fixed-effects models to estimate the effects of the content richness of constraining descriptions disclosure on review numbers and review scores. To test Hypotheses 1a, 1b, and 2, the models were constructed as follows:

$$Review\_num_{it} = \beta_0 + \beta_1 Topic\_num_{it} + \beta_2 Control_{it} + \mu_i + v_t + \varepsilon_{it}. \tag{1}$$

$$Review\_score_{it} = \beta_0 + \beta_1 Topic\_num_{it} + \beta_2 Control_{it} + \mu_i + v_t + \varepsilon_{it}. \tag{2}$$

For the above model, i represents listing and t represents month. $Review\_num_{it}$ and $Review\_score_{it}$ refer to the number of reviews the listing i received on month t and the review score rating of listing i received on month t, respectively. $Topic\_num_{it}$ represents the number of topics of listing i disclosed in house rules on month t. $Control_{it}$ includes all control variables shown in Table 1 to control some time-varying, listing-level heterogeneity. μ_i is the listing-level fixed effect, and v_t is a month-level fixed effect. $Control_{it}$ is a vector that includes all control variables reported in Table 1, and β_2 is a vector that includes the coefficients of corresponding control variables. Table 4 shows that the standard deviations of *Competition, Listing_count*, and *Price* are relatively high. Therefore, we took the logarithm of the three variables in the model to slow the fluctuation of the sample data and encourage the normal distribution of data (Zhang et al., 2019).

We expanded Eqs. (3) and (4) by introducing several interaction terms to further verify the moderating effect of Hypotheses 3a, 3b, 4a, 4b, 4c, 5a, and 5b.

$$\begin{aligned} Review\_num_{it} = {} & \beta_0 + \beta_1 Topic_{num\,it} + \beta_2 LogCompetition_{it} + \beta_3 l.Superhost_{it} \\ & + \beta_4 LogPrice + \beta_5 Topic_{num\,it} \times LogCompetition_{it} \\ & + \beta_6 Topic_{num\,it} \times \ l.Superhost_{it} + \beta_7 Topic_{num\,it} \times LogPrice \\ & + \beta_6 Control_{it} \ + \mu_i + v_t + \varepsilon_{it} \quad , \end{aligned} \tag{3}$$

$$\begin{aligned} Review\_score_{it} = {} & \beta_0 + \beta_1 Topic_{num\,it} + \beta_2 LogCompetition_{it} + \beta_3 l.Superhost_{it} \\ & + \beta_4 LogPrice + \beta_5 Topic_{num\,it} \times LogCompetition_{it} \\ & + \beta_6 Topic_{num\,it} \times \ l.Superhost_{it} + \beta_7 Topic_{num\,it} \times LogPrice \\ & + \beta_6 Control_{it} \ + \mu_i + v_t + \varepsilon_{it} \quad . \end{aligned} \tag{4}$$

5. Results

5.1. Latent dirichlet allocation analysis

This study used the number of topics rather than text length to measure the content richness of house rules. This option was chosen because hosts are likely to use many words to repeat one topic, and thus, the number of topics can better measure the degree to which the hosts disclosed the constraining descriptions (Jia, 2020; Zhang et al., 2019). This article is based on the *gensim* package of Python language for Latent Dirichlet Allocation (LDA) topic extraction. After cleaning the text corpus of the original house rules, we inputted them into the LDA training model and obtained eight types of house rules topics. After debugging the number of keywords combined with word semantics, we outputted five keywords associated with each topic type. The final topic recognition results are shown in Table 2.

Table 2 shows that the description of the shared accommodation housing rules involves many aspects, such as fees, check-in time, respect for others, keeping clean, and so on. This study summarized the house rules based on the results generated by the LDA model and realistic semantics to make the topic identification more realistic and better guide the practice. Finally, the rules were summarized into four categories: *Civilization-related*, *Living conditions*, *Personal activities*, and *Host management* (shown in Table 3). Among them, the topic of *Civilization-related* requires guests to get along well with the surrounding neighbors and other guests in the same house, including keeping quiet, being friendly, and being respectful to the neighbors. The topic of *Living conditions* requires guests to keep the room in good condition during their stay and includes keeping the house clean and tidy (including the bedroom, kitchen, floor, etc.), prohibiting guests from wearing shoes, and carrying out diet-related activities (e.g., cooking indoors, etc.). The *Personal activities* topic requires guests to pay attention to their own words and behaviors to avoid potential safety hazards and illegal behaviors, including specific regulations on smoking (e.g., no smoking), rules on party behavior (e.g., no parties), rules on pet keeping (e.g., no pets), and other illegal behaviors. The topic of *Host management* refers to the host's management regulations on the guest's reservation and check-in process. It includes the check-in and check-out times, the rules of the booking platform (e.g., prohibiting booking from a third-party platform), and restrictions of visitors (e.g., prohibiting overnight guests).

Fig. 2 further shows the topic distribution of each house rule disclosed. The columns at the bottom (dark blue) represent the proportion

Table 2
LDA model training results.

Topic	Words
Topic 1	"guest," "book," "allow," "addict," "extra"
Topic 2	"guest," "fee," "charge," "check," "key"
Topic 3	"home," "respect," "apart," "treat," "guest"
Topic 4	"clean," "leave," "shoe," "dish," "kitchen"
Topic 5	"check," "time," "fee," "late," "arrive"
Topic 6	"quiet," "loud," "hour," "music," "noise"
Topic 7	"space," "common," "area," "house," "clean"
Topic 8	"smoke," "allow," "party," "apart," "pet"

Table 3
House rules topic type.

Topic	Content
Civilization related	(1) Keep quiet (2) Respect neighbors
Living conditions	(1) Keep it tidy (2) Take off your shoes when entering the room (3) Cooking related
Personal activities	(1) Smoking (2) Party (3) Pet
Host management	(1) Check-in/check-out time (2) Booking platform (3) Visitors
Others	Other content not mentioned above

Table 4
Descriptive statistics results of related variables.

Variable	Mean	Std. Dev.	Min	Max
Reviews_num	28.838	53.733	0	995
Review_score	4.720	0.420	1	5
If_have_houserules	0.825	0.380	0	1
Topic_num	1.671	1.250	0	4
Competition	692.315	623.264	0	4360
Superhost	0.261	0.439	0	1
Private_room	0.372	0.483	0	1
Shared_room	0.029	0.167	0	1
Hotel_room	0.004	0.065	0	1
Accommodates	3.459	2.520	0	40
Amenities	23.658	11.535	0	130
Beds	1.859	1.640	0	132
Price	203.584	578.390	0	25,000
Listing_count	23.650	147.543	0	2345
Localhosts	0.597	0.490	0	1
Cancellation	2.140	0.849	1	3
Description	135.124	56.772	1	284
Photo	0.278	0.448	0	1
Covid	64.898	234.458	0	3589

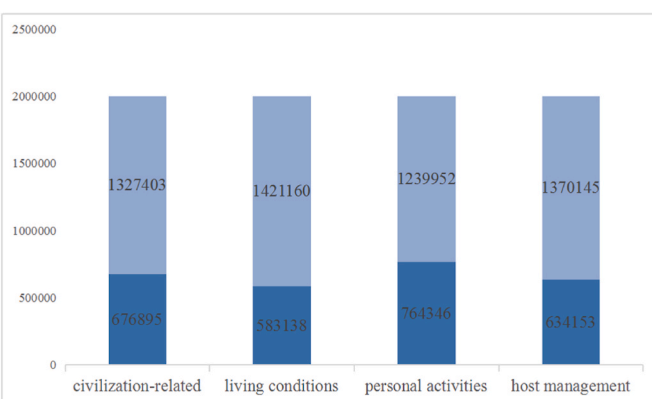

Fig. 2. Sample distribution of hosts' constraining description disclosure by topic.

of hosts who have disclosed this topic of constraining descriptions to the platform. Hosts are shown to be more likely to disclose personal activities information on the platform, such as regulations on smoking (e.g., no smoking), rules on party behavior (e.g., no parties), rules on pet keeping (e.g., no pets), and other illegal behaviors. By contrast, only 29% of the hosts would post living condition topics. Such findings can help academic scholars and platform managers gain a better understanding of the real writing pattern of constraining descriptions for Airbnb hosts.

5.2. Summary statistics

Table 4 shows the descriptive statistics results of the relevant variables. The results show that the average number of reviews received for each listing is 23.784, the average user rating is 4.693, and 60% of the listings have disclosed constraining descriptions. Specifically, the average house rules contain 1.167 topics.

Because monthly data were used, a time series plot was drawn to show the seasonality in the data (Figs. 3 and 4). Overall, the number of reviews showed an upward trend over time, especially from August to September, which corresponds well to the seasonality. In addition, since March 2020, the spread of COVID-19 has caused a decline in the number of bookings of Airbnb listings, whereas guest satisfaction presents a stable state. Nevertheless, a clear downward trend is observed from July to September. Furthermore, to determine the spatial relationship between single Airbnb listings, we drew heatmaps for each city based on their listing distribution (Fig. 5). The heatmaps indicate that in all cities, the listings tended to cluster in the center, and for seaside and lakeside cities, such as Los Angeles and Chicago, listings are more likely to be distributed along the coast.

We used the variance inflation factor (VIF) test and the correlation coefficient matrix to conduct a collinearity analysis on all explanatory variables. The results show that the variance expansion factors of each explanatory variable are all less than 10, and the correlation coefficients are all less than 0.8, indicating that no significant correlation was observed between the independent and control variables. Thus, multicollinearity cannot affect the accuracy of our empirical results.

5.3. Empirical results

The empirical results of Equation (1) are shown in the first two columns of Table 5. Specification 1 for Table 5 represents the results without controlling the listing-fixed and month-fixed effects while Specification 2 reports results based on models including the two fixed effects. The results show that the topic number of the constraining description of listings is significantly positively associated with review volume, and thus, Hypothesis 1a is verified. We constructed Equation (3) to further verify the moderating effects of competition intensity, host reputation, and price on guests' booking decisions, which are stated in Hypotheses 3a, 4a, 4b, and 5a. The results in the last two columns of Table 5 show that the coefficients of the interaction between competition intensity and *Topic_num* are negative and significant, while the interaction between *Superhost* and *Topic_num* is positive and significant. This outcome indicates that the positive effect of *Topic_num* on review volume is amplified when listings have low competition intensity, and/or the host is identified as a "Superhost," thereby supporting Hypotheses 3a, 4a. However, although the coefficient of the interaction between price and *Topic_num* is negative, it becomes insignificant after controlling the fixed effect of listing and month, and thus, Hypothesis 5a is not supported.

This study constructed Equation (2) to ensure a better understanding of the effects of the mechanism of constraining description on guests' satisfaction. The results are shown in Table 6. The first two columns show that the coefficients between *Topic_num* and *Review_score* are negative and significant, which verifies Hypothesis 2. Similarly, we used Equation (4) to further verify Hypotheses 3b, 4c, and 5b. The results in the last two columns of Table 6 show that the coefficients of the interaction between competition intensity and *Topic_num* and that between *Superhost* and *Topic_num* are both positive and significant, while the interaction between price and *Topic_num* is negative and significant, thereby supporting Hypotheses 3b, 4c, and 5b.

5.4. Robustness check

We conducted a series of robustness checks using different measurements of independent and dependent variables to further check the robustness of our empirical results. First, the panel regression model with robust standard errors was used to check the robustness, and the results are highly consistent with the results based on basic models (see

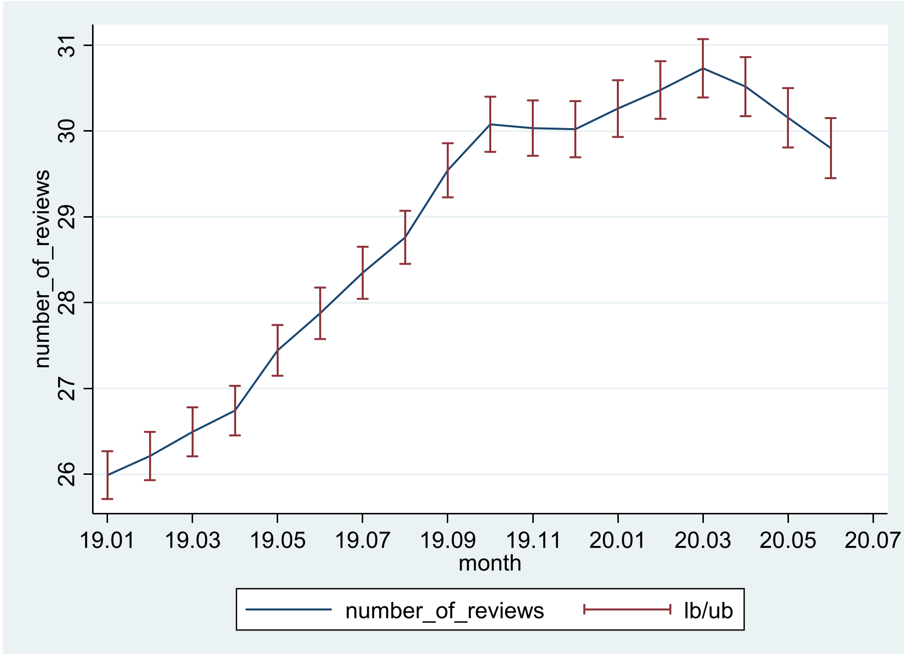

Fig. 3. Time series plots for *Review_num*.

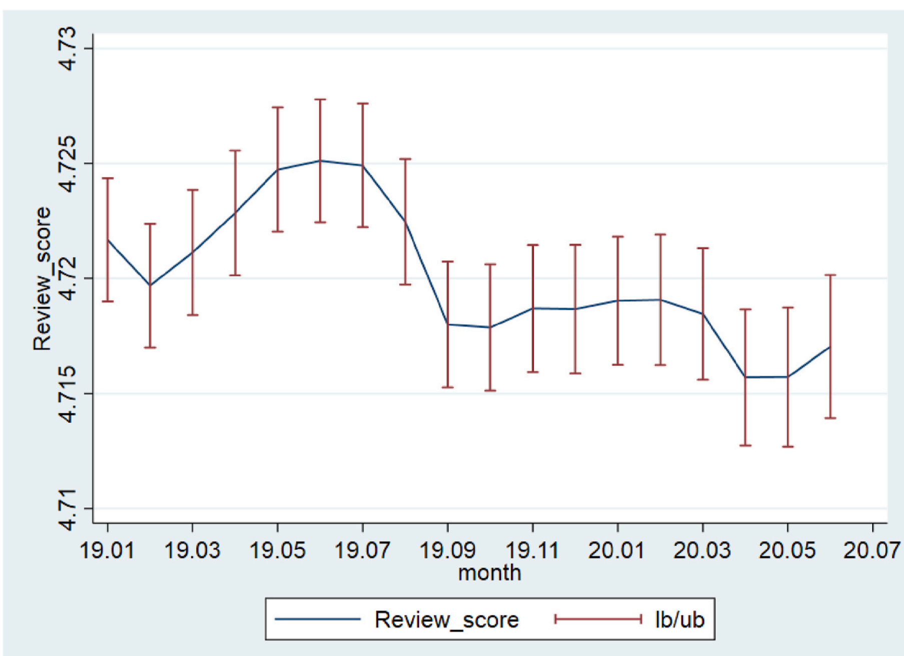

Fig. 4. Time series plots for *Review_score*.

Table 7). Second, we also used the average text length of each topic (*WordPerTopic*) as an alternative measure of topic number (see Table 8). According to previous research (Liang et al., 2020), the measurement for the content of information disclosure always contains two aspects, namely, width (number of topics covered by the description) and depth (text length). Thus, this new variable can measure the content richness of house rules from the perspective of width and depth. Third, some hosts tend to use bullet points to preset their house rules. Hence, we also use the number of sentences for house rules (*Sentence*) as the proxy for constraining description disclosure. The results are presented in Table 9. Except for the significance level of several moderating effects, the meanings of most variables are consistent with the baseline model.

Fourth, for the four topics of house rules, we also attempted to use the text length of each topic as an alternative measure of constraining description (see Table 10). The result shows that even though we used some alternative measures of independent variables, the results are highly consistent with those based on basic models. Additionally, the text length of topics related to host management, such as check-in/check-out time, booking platform, and visitors' regulations have the greatest positive effect on guests' booking decisions compared with the text length of other topics while the topic on host management and personal activities, such as smoking, party, and pet regulations, had the

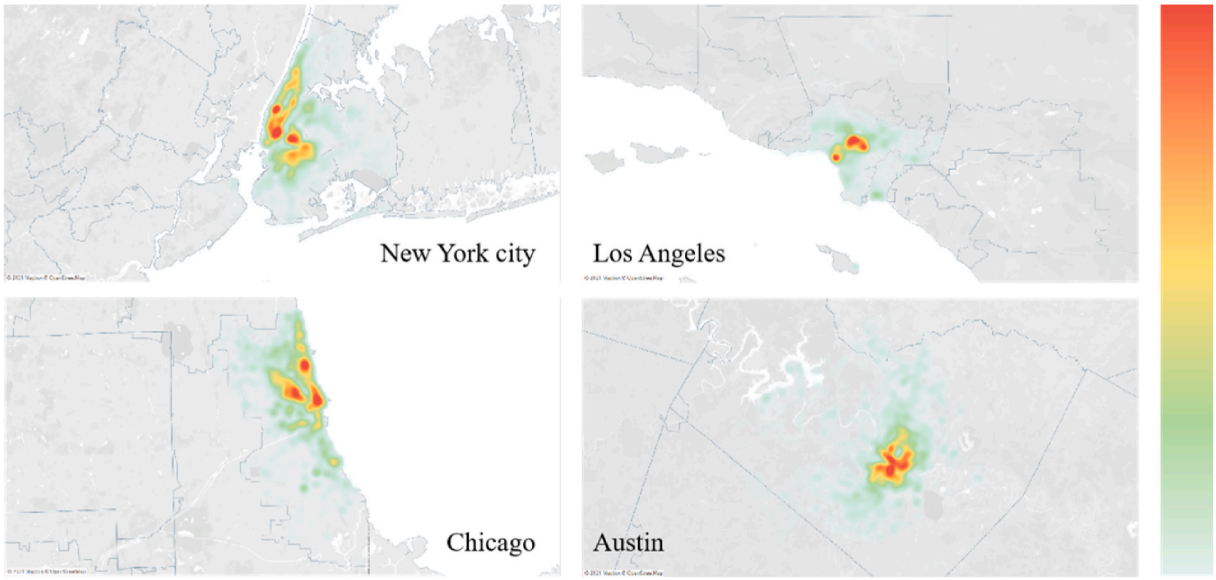

Fig. 5. Heatmaps of New York city, los Angeles, Chicago, and Austin.

Table 5
Estimation results of guests' purchase booking decisions.

	Model 1		Model 3	
	Spec 1	Spec 2	Spec 1	Spec 2
Topic_num	3.9745*** (119.87)	2.0118*** (64.91)	3.7298*** (110.62)	1.7986*** (56.96)
LogCompetition	−5.2382*** (−140.45)	−0.8853*** (−21.66)	−5.562*** (−146.70)	−1.23*** (−29.48)
Superhost	1.8619*** (51.14)	0.8419*** (26.33)	1.8609*** (50.89)	0.8341*** (25.97)
LogPrice	−0.4117*** (−5.73)	−0.0025 (−0.03)	−0.4297*** (−5.99)	−0.0387 (−0.54)
Topic_num×LogCompetition			−0.9881*** (−46.14)	−0.7855*** (−40.33)
Topic_num×Superhost			−0.0148 (−0.54)	0.0467* (1.92)
Topic_num×LogPrice			−0.2163*** (−6.76)	−0.0185 (−0.63)
Private_room	−1.3938*** (−10.65)	0.5187*** (3.99)	−1.4051*** (−10.74)	0.5089*** (3.91)
Shared_room	−6.4641*** (−22.99)	−1.9387*** (−7.00)	−6.3361*** (−22.55)	−1.8615*** (−6.72)
Hotel_room	5.7788*** (27.55)	1.77*** (9.30)	5.7861*** (27.6)	1.8004*** (9.46)
Accommodates	−0.7672*** (−30.10)	−0.2181*** (−8.72)	−0.7597*** (−29.83)	−0.2101*** (−8.40)
Amenities	0.6496*** (206.22)	0.2534*** (86.53)	0.6473*** (205.53)	0.252*** (86.08)
Beds	−0.156*** (−5.80)	0.0356 (1.44)	−0.1653*** (−6.15)	0.0284 (1.15)
LogListing_count	0.7523*** (17.36)	1.327*** (29.31)	0.7394*** (17.08)	1.3121*** (29.00)
Localhost	4.6503*** (48.96)	1.4188*** (15.60)	4.661*** (49.11)	1.4244*** (15.68)
Cancellation	2.3506*** (66.71)	0.9148*** (28.80)	2.3625*** (67.08)	0.9245*** (29.12)
Description	0.034*** (98.40)	0.011*** (35.90)	0.034*** (98.25)	0.011*** (36.00)
Photo	7.5334*** (104.93)	2.2638*** (34.25)	7.5295*** (104.95)	2.2756*** (34.44)
Covid	0.0073*** (177.88)	0.0004*** (8.89)	0.0072*** (177.76)	0.0004*** (9.37)
Listings FE	N	Y	N	Y
Month FE	N	Y	N	Y
N	1,555,476	1,555,476	1,555,476	1,555,476

Note: Coefficients are shown in the table; t values are shown in parentheses. *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

greatest effect on reducing guest satisfaction.

Fifth, although we measured guest booking decisions using review volume, consistent with prior studies such as Liang, Zhang, Li, Li, and Yu (2021) and Xie and Mao (2017), we used property demand as the alternative measurement of dependent variables. Property demand was measured by the number of booked days for the next 30, 60, and 90 days. The results are also highly consistent with the basic model, indicating the good sensitivity of our results (Table 11). In addition, although we controlled listing-level fixed effect and month-level fixed effect, some confounding effects for some independent variables may still occur because of reverse causality issues. For example, the positive effect of "Superhost" status on guest satisfaction may be because properties with high guest satisfaction are more likely to get the "Superhost" badge. Accordingly, to be consistent with prior studies, such as Zhang, Zhang, et al. (2021), we changed all independent variables to their lagged term to avoid the influence of reverse causality issue. The results are presented in Table 12. Except for some moderating effects becoming insignificant, the meanings of most variables are still consistent with the baseline model.

Finally, in some studies, hosts who owned more than four Airbnb listings were identified as commercial hosts (Gyódi & Nawaro, 2021). The host behavior of posting a constraining description may differ from that of other hosts. Thus, we conducted a subsample analysis by removing all hosts with more than four listings. The results are shown in Table 13, and the main results are still the same as our basic model.

6. Discussion and implications

6.1. Main findings

Prior studies have confirmed the effectiveness of information disclosure through service providers and marketer-generated content on

Table 6
Estimation results of guest satisfaction.

	Model 2		Model 4	
	Spec 1	Spec 2	Spec 1	Spec 2
Topic_num	−0.0061*** (−15.75)	−0.0075*** (−17.91)	−0.0061*** (−15.29)	−0.0075*** (−17.70)
LogCompetition	0.0096*** (21.42)	0.0041*** (7.24)	0.0098*** (21.62)	0.0042*** (7.40)
Superhost	0.0196*** (48.99)	0.0161*** (40.26)	0.0194*** (48.35)	0.0159*** (39.57)
LogPrice	0.009*** (10.11)	0.0001 (0.10)	0.0092*** (10.21)	0.0003 (0.25)
Topic_num×LogCompetition			0.0009*** (3.42)	0.0006** (2.12)
Topic_num×Superhost			0.0008** (2.45)	0.001*** (3.39)
Topic_num×LogPrice			−0.0006 (−1.60)	−0.0007* (−1.74)
Private_room	−0.0032** (−2.07)	0.0034** (1.95)	−0.0032** (−2.08)	0.0034* (1.94)
Shared_room	−0.0525*** (−15.48)	−0.0137*** (−3.64)	−0.0525*** (−15.49)	−0.0137*** (−3.64)
Hotel_room	−0.035*** (−13.65)	−0.0121*** (−4.58)	−0.0351*** (−13.67)	−0.0121*** (−4.59)
Accommodates	0.0002 (0.79)	0.0012*** (3.51)	0.0002 (0.75)	0.0012*** (3.49)
Amenities	0.0001 (1.22)	−0.0001** (−2.4)	0.0001 (1.28)	−0.0001** (−2.37)
Beds	−0.0006* (−1.92)	0.0002 (0.75)	−0.0006* (−1.91)	0.0002 (0.76)
LogListing_count	−0.0184*** (−34.83)	−0.0027*** (−4.47)	−0.0184*** (−34.81)	−0.0027*** (−4.46)
Localhost	0.0009 (0.78)	−0.0084*** (−6.86)	0.0009 (0.78)	−0.0084*** (−6.86)
Cancellation	−0.0111*** (−26.63)	−0.0089*** (−20.91)	−0.0111*** (−26.64)	−0.0089*** (−20.92)
Description	0.0001*** (−4.04)	0.0001** (−2.33)	0.0001*** (−4.05)	0.0001** (−2.36)
Photo	−0.0206*** (−24.92)	−0.0074 (−8.5)	−0.0206*** (−24.91)	−0.0074*** (−8.51)
Covid	0.0001*** (−15.46)	0.001** (2.18)	0.0001*** (−15.46)	0.0001** (2.13)
Listings FE	N	Y	N	Y
Month FE	N	Y	N	Y
N	1,266,222	1,266,222	1,266,222	1,266,222

Note: Coefficients are shown in the table; t values are shown in parentheses. *p < 0.1, **p < 0.05, and ***p < 0.01.

Table 7
Robustness check 1: Estimation results with robust standard errors.

	Review_num		Review_Score	
	Model1	Model3	Model2	Model4
Topic_num	2.0118*** (19.61)	1.7986*** (17.33)	−0.0075*** (−6.88)	−0.0075*** (−6.86)
LogCompetition	−0.8853*** (−7.34)	−1.23*** (−9.37)	0.0041*** (3.00)	0.0042*** (3.20)
Superhost	0.8419*** (9.78)	0.8341*** (9.78)	0.0161*** (25.71)	0.0159*** (24.82)
LogPrice	−0.0025 (−0.01)	−0.0387 (−0.22)	0.0001 (0.04)	0.0003 (0.09)
Topic_num×LogCompetition		−0.7855*** (−12.48)		0.0006 (0.84)
Topic_num×Superhost		0.0467 (0.67)		0.001** (2.03)
Topic_num×LogPrice		−0.0185 (−0.22)		−0.0007 (−0.61)
Control Variables	Y	Y	Y	Y
Listings FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Robust	Y	Y	Y	Y
N	1,555,476	1,555,476	1,266,222	1,266,222

Note: Coefficients are shown in the table; t values are shown in parentheses. *p < 0.1, **p < 0.05, and ***p < 0.01.

Table 8
Robustness check 2: Alternative measure of independent variables: average text length of each topic as proxy.

	Review_num		Review_Score	
	Model1	Model3	Model2	Model4
WordPerTopic	0.0376*** (23.69)	0.0344*** (21.17)	−0.0003*** (−17.58)	−0.0004*** (−18.78)
LogCompetition	−1.5003*** (−27.68)	−1.3565*** (−24.93)	0.0038*** (5.87)	0.0036*** (5.57)
Superhost	0.7867*** (21.66)	0.7784*** (21.43)	0.0157*** (38.2)	0.0155*** (37.83)
LogPrice	−0.2697*** (−3.29)	−0.0057 (−0.07)	−0.0004 (−0.43)	−0.0007 (−0.64)
WordPerTopic ×LogCompetition		−0.0303*** (−29.37)		0.001** (2.44)
WordPerTopic ×Superhost		0.0087*** (6.68)		0.0002*** (10.58)
WordPerTopic ×LogPrice		−0.0263*** (−18.98)		0.0001 (1.17)
Control Variables	Y	Y	Y	Y
Listings FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	1,243,212	1,243,212	1,050,895	1,050,895

Note: Coefficients are shown in the table; t values are shown in parentheses. *p < 0.1, **p < 0.05, and ***p < 0.01.

product and service performance (Dedeke, 2016; Goh et al., 2013; Hernández-Ortega, San Martin, Herrero, & Franco, 2020). Several recent studies have also noted that information disclosed by property hosts in peer-to-peer rental platforms is more important because of the particularities of such platforms (e.g., Liang et al., 2020). This study takes a step further by focusing specifically on one type of host information disclosure called constraining description. Constraining description has rarely been disclosed by service providers in traditional online travel agencies because, as a type of negative information, it may arouse the negative sentiment of consumers, which would then

Table 9
Robustness check 3: Alternative measure of independent variables: number of sentences as proxy.

	Review_num		Review_Score	
	Model1	Model3	Model2	Model4
Sentence	0.3231*** (51.36)	0.2562*** (38.72)	−0.0015*** (−16.6)	−0.0017*** (−17.58)
LogCompetition	−1.5443*** (−41.05)	−1.5872*** (−42.19)	0.0033*** (6.06)	0.0033*** (6.04)
Superhost	1.0449*** (36.35)	1.0438*** (36.1)	0.0158*** (41.63)	0.0154*** (40.27)
LogPrice	−0.0345 (−0.53)	−0.0427 (−0.65)	0.0005 (0.51)	0.0006 (0.61)
Sentence ×LogCompetition		−0.1888*** (−41.93)		−0.0001 (−1.04)
Sentence×Superhost		−0.0038 (−0.67)		0.0007*** (8.59)
Sentence×LogPrice		0.004 (0.65)		−0.0001 (−1.00)
Control Variables	Y	Y	Y	Y
Listings FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	1,879,008	1,879,008	1,491,089	1,491,089

Note: Coefficients are shown in the table; t values are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 10
Robustness check 4: Categorical measure of independent variables.

	Model 1		Model 2	
	Spec 1	Spec 2	Spec 1	Spec 2
Civilization related	2.6145 *** (28.83)	1.4186*** (16.37)	0.0042*** (3.75)	−0.0030** (−2.49)
Living conditions	2.2234 *** (28.02)	0.7751*** (10.42)	−0.0064 *** (−6.43)	−0.0080*** (−7.72)
Personal activities	4.2975 *** (50.91)	2.3009*** (28.94)	−0.0065 *** (−6.20)	−0.0092*** (−8.25)
Host management	5.6673 *** (73.18)	3.2636*** (45.46)	−0.0120 *** (−12.41)	−0.0102*** (−10.18)
Control Variables	Y	Y	Y	Y
Listings FE	N	Y	N	Y
Month FE	N	Y	N	Y
N	1,880,275	1,880,275	1,491,990	1,491,990

Note: Coefficients are shown in the table; t values are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 11
Robustness check 5: Alternative measure of dependent variable.

	Booked_30		Booked_60		Booked_90	
	Spec 1	Spec 2	Spec 1	Spec 2	Spec 1	Spec 2
Topic_num	0.0216 (−0.82)		0.2519*** (5.19)		0.6134*** (9.01)	
WordPerTopic		0.0021 (1.58)		0.0052** (2.16)		0.0112*** (3.29)
Control Variable	Y	Y	Y	Y	Y	Y
Listings FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
N	1,555,476	1,243,212	1,555,476	1,243,212	1,555,476	1,243,212

Note: Coefficients are shown in the table; t values are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 12
Robustness check 6: Lagged independent variables.

	Review_num		Review_Score	
	Model1	Model3	Model2	Model4
l.Topic_num	2.0458*** (63.76)	1.8486*** (56.51)	−0.0065*** (−16.79)	−0.0066*** (−16.56)
l.LogCompetition	1.0311*** (31.53)	1.0236*** (31.17)	0.0097*** (25.47)	0.0095*** (24.9)
l.Superhost	−0.7469*** (−17.74)	−1.0441*** (−24.33)	0.0032*** (5.90)	0.0033*** (6.04)
l.LogPrice	−0.1371* (−1.79)	−0.1752** (−2.29)	−0.0026*** (−2.64)	−0.0026*** (−2.63)
l.Topic_num×l.LogCompetition		−0.7026*** (−35.12)		0.0004 (1.58)
l.Topic_num×l.Superhost		0.0378 (1.51)		0.0011*** (3.62)
l.Topic_num×l.LogPrice		0.0359 (1.17)		−0.0001 (−0.24)
Control Variables	Y	Y	Y	Y
Listings FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	1,379,405	1,379,405	1,151,339	1,151,339

Note: Coefficients are shown in the table; t values are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

negatively affect their purchasing decisions (Siegenthaler & O'Dell, 2000). However, such information is necessary for service providers in peer-to-peer rental platforms because guests only purchase the right of use rather than ownership of accommodations; thus, hosts may sometimes have to regulate guest behavior by announcing constraining items, such as "house rules" (Cheng & Zhang, 2019; Jiang, Balaji, & Jha, 2019; Yao et al., 2019). The current study is one of the early attempts to observe how this special type of information disclosed by the host affects guest behavior and host performance.

First, we find that the basic types of constraining description actively

Table 13
Robustness check 7: Remove the impact of commercial host.

	Review_num		Review_Score	
	Model1	Model3	Model2	Model4
Topic_num	3.0595*** (69.71)	2.6936*** (59.76)	−0.009*** (−19.08)	−0.0094*** (−19.5)
LogCompetition	−0.2216*** (−4.01)	−0.4105*** (−7.4)	0.0016*** (2.70)	0.0015*** (2.56)
Superhost	1.6801*** (45.81)	1.6486*** (44.79)	0.0138*** (37.53)	0.0137*** (37.23)
LogPrice	0.8252*** (8.21)	0.8200*** (8.16)	0.0005 (0.42)	0.0005 (0.48)
Topic_num×LogCompetition		−0.9298*** (−36.47)		−0.0013*** (−4.63)
Topic_num×Superhost		0.2175*** (7.5)		0.0002 (0.56)
Topic_num×LogPrice		−0.3585*** (−7.77)		−0.0005 (−0.94)
Control Variables	Y	Y	Y	Y
Listings FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	1,164,283	1,164,283	956,898	956,898

Note: Coefficients are shown in the table; t values are shown in parentheses. *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

disclosed by the listing owners include civilization-related, living conditions, personal activities, and host management. Unlike traditional hotels, shared accommodations often lack training in guest management and a unified standard to manage guests (Liang et al., 2021). Thus, they are more likely to suffer a loss when encountering service failure and accommodating guests who exhibit unethical behavior (Ma, Gu, Hampson, & Wang, 2020). In this study, we find that over 60% of hosts tend to disclose constraining descriptions to regulate guest behavior before their bookings. Many hosts (over 31%) have disclosed regulations related to the topics of guest activities, such as specific regulations on smoking (e.g., No smoking).

Second, we further verify the effects of constraining description on guest behavior and host performance. We find that guests' booking decisions, as represented by review volume and demand, increase when hosts disclose more detailed house rules (more topics are included). Although the constraining description may arouse negative sentiment in some leisure tourists who desire freedom (Agyar, 2014), more detailed information from different perspectives can be attractive for guests because it helps reduce uncertainties (Xu et al., 2021). However, disclosing detailed constraining descriptions can have negative effects on guest satisfaction because it could increase their expectations.

This study also explores the moderating effects of external competition intensity, host reputation, and price. The results show that when hosts face high external competition intensity, the positive effect of disclosing constraining descriptions on guest booking decisions and its negative effect on guest satisfaction is weakened. This finding indicates that more choices and limited energies cause guests to focus more attention on other direct information cues related to service quality, thereby weakening the overall effects of indirect information cues, such as house rules on guest decisions and satisfactions (Zhang et al., 2019). We also find that if hosts are identified as "Superhosts" by platform managers, then the benefits of more detailed house rules will be higher than those of other hosts. The positive effects of disclosing constraining descriptions on review volume and property demand are amplified and the negative effects on guest satisfaction are weakened. Finally, we report the moderating effects of price as additional findings. The results indicate that the negative effects of more detailed house rules on guest satisfaction will be amplified if property owners set a relatively high price.

6.2. Theoretical and managerial implications

First, the findings of this study contribute to the literature related to information disclosure on electronic commerce platforms. This study is one of the first attempts to focus on a specific type of information disclosed by service providers. This type of information, namely, constraining description, can rarely be found in the context of traditional electronic commerce platforms and online travel agencies.

Prior studies have already noted the importance of disclosing product or service information on consumer purchasing decisions and product or service performance in the context of traditional electronic commerce platforms and online travel agencies (Goh et al., 2013; Lv, Li, & Xia, 2020). Some prior studies have also compared the effects of user- and marketer-generated content on product or service performance (Song, Huang, Tan, & Yu, 2019; Tsiakali, 2018). However, the consequences of providing the new type of information (constraining description) have not been explored in prior studies.

Based on the identification of particularities in an emerging market, which is peer-to-peer rental platforms, the present study analyzed the effects of disclosed constraining description on subsequent guest booking decisions and satisfaction by expanding and modifying relevant theories, such as rational choice theory, based on the particularities of the new context. Accordingly, the results of this study can present new insights for future studies that focus on the effects of constraining descriptions based on other emerging contexts. For example, further studies can observe how constraining description disclosure affects consumer purchasing decisions in the context of the online medical market.

Second, this study presents theoretical implications to the literature on peer-to-peer rental platforms because it is also an early attempt to observe how the information disclosure behavior (information description posting) of hosts affect subsequent guest booking decisions and satisfaction. Many prior studies have discovered how the particularities of peer-to-peer rental platforms, as a type of emerging context, affect users and behavioral patterns. For example, some studies have noted that because of the limited supply of user-generated content and the existence of positive bias, the effects of information disclosed by hosts are more important for peer-to-peer rental platforms than for other traditional online travel agencies (Liang et al., 2020). Accordingly, several studies have confirmed how host textual descriptions and selfies affect their performance (Barnes & Kirshner, 2021; Zhang, Yan, & Zhang, 2020). However, to the best of our knowledge, no study has focused on the effects of a specific type of information disclosed by hosts on guest behaviors and the mechanism behind such effects. Thus, this study also provides new insights for literature related to peer-to-peer rental platforms to focus on the determinants of guest booking decisions and satisfaction from the perspective of host information disclosure.

The practical implications of this study are threefold. First, for guests, this research provides some guidance for information search and comparison and their decision-making process before making booking decisions, which is conducive to helping the guests make better choices. Guests should read the information on the house rules disclosed carefully to understand the restrictions during the living process and host preferences and make decisions according to their preferences. However, posting detailed constraining descriptions should not be treated as a direct information cue of high service quality and expectations should be reasonably adjusted to avoid satisfaction loss. Second, property owners should understand the trade-offs of disclosing detailed house rules. Although it can attract more bookings, such disclosure may hurt the property's reputation and negatively affect its performance in the long term. Accordingly, properties owners cannot rely on constraining descriptions alone to improve their performance because it is more beneficial to property performance only when hosts face low competitive intensity and have a high level of service quality. They should disclose other direct information cues related to their service quality and constantly improve their service quality to increase guests' perceived performance after consumption.

Finally, as noted above, although constraining description can affect guest booking decisions, satisfaction, and host performance, most hosts disclose such information to regulate guest behavior and protect property safety rather than improve performance. However, given the direct effect of constraining description on review volume and demands, platform managers can further encourage property owners to disclose house rules by developing incentive mechanisms, such as assigning virtual badges to improve the trading values of the entire platform.

6.3. Limitations and further research

This study has several limitations. First, it only focused on listings in the United States. Given that users in different regions may have different behavioral patterns because of different cultural backgrounds, future studies can expand our study by observing how effective constraining description is in other countries. Second, this study only chose Airbnb as our research context because of its representativeness. Thus, future studies can also collect data from other peer-to-peer rental platforms using different online designs and observe whether different online designs in platforms affect the main results. Third, although we have controlled most property and host characteristics that could be found publicly in the websites and property and month fixed effects, some confounding and time-varying factors that may influence our results could still be found. Hence, future studies can further try to collect other factors, such as hosts' income, by combining secondary data with a large-scale survey to further validate the accuracy of the results. Finally, we used LDA models to measure the independent variables. However, such methods may be less effective when analyzing short text. Future studies can consider using other text mining approaches, such as establishing a text dictionary that includes constraining-related words to better measure the degree that hosts disclosed containing description.

Credit author statement

Lanfei Gao conducted the empirical analysis of the paper. She also presented the descriptive statistics of the results and provided the motivation of this paper. Hui Li reviewed the relevant literature, and was responsible for the methodology and part of results. Sai Liang collected and cleaned the data along with the interpretation of the results and conclusions. He also helped finish the introduction and hypotheses part. Jingjing Yang contributed to part of conceptualization and validation. She also helped proofread the paper. Rob Law contributed to part of results and conclusion. He also helped edit the paper in general.

Impact statement

Several studies have investigated the effects of different information sources, such as online reviews on guest behavior in the context of peer-to-peer rental platforms, and some of them have highlighted the importance of host-generated content and its effects in guest behavior and host performance. However, the particularities of sharing economy platforms allow service providers (property hosts) to disclose a kind of negative and constraining information to regulate guest behaviors, and to the best of our knowledge, none of the prior studies have focused on the effects of this specific disclosed information on subsequent guest behavior and host performance. Through collecting a unique longitudinal dataset covering 90,322 Airbnb listings from January 2019 to June 2020, this study constructed panel regression models with fixed effects to observe how the dynamic changes in house rules affect guest attention and satisfaction. As one of the earliest attempts to focus on the effects of constraining information disclosure (e.g. house rules on Airbnb) on guest behavior, this study provides new insights into future studies targeting another specific type of host-generated content. The results of this study also provide practical implications to property owners and platform managers to help them understand how to improve performance and matching efficiency by adjusting the strategies of constraining information disclosure.

Declaration of competing interest

None.
Liang et al., 2017

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