The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/0959-6119.htm

Received 20 October 2021
Revised 14 February 2022
16 April 2022
17 April 2022
Accepted 23 April 2022

Cue congruence effects of attribute performance and hosts' service quality attributes on room sales on peer-to-peer accommodation platforms

Dongzhi Chen
Business School, Tianjin University of Finance and Economics, Tianjin, China, and
Jian-Wu Bi
College of Tourism and Service Management, Nankai University, Tianjin, China

Abstract

Purpose – This study aims to explore how attribute performance and hosts' service quality attributes affect room sales on peer-to-peer (P2P) platforms from the cue congruence perspective.

Design/methodology/approach – More than 9.53 million reviews concerning 258,473 listings located in 35 major cities worldwide were collected from Airbnb. Data was collected from December 2019 to December 2020 and was analysed using a generalised linear model.

Findings – Results show that when attribute performance and hosts' service quality attributes give positive signals, Airbnb room sales are significantly higher than when the two kinds of cues give inconsistent or negative signals; when attribute performance gives positive signals and hosts' service quality attributes give negative signals, room sales are higher than when the former gives negative signals and the latter give positive signals; surprisingly, when both kinds of cues give negative signals, room sales are higher than when attribute performance gives positive signals and hosts' service quality attributes give negative signals.

Research limitations/implications – This paper adds useful insights on understanding of cue congruence (incongruence) effect on room sales of P2P accommodation platforms. This study has practical implications for hosts, online platform managers and guests regarding how to use online strategies and promotions on the Airbnb platform.

Originality/value – This study is an early attempt to explore how the combination of attribute performance and hosts' service quality attributes affects Airbnb room sales under the conditions of consistency and inconsistency.

Keywords Cue congruence, Attribute performance, Hosts' service quality attributes, Room sales, Justice-based theory

Paper type Research paper

1. Introduction

The peer-to-peer (P2P) platforms that allow individuals to market their homestays are developing rapidly (De Canio *et al.*, 2020; Xie *et al.*, 2021). However, without face-to-face

This work was partly supported by the National Natural Science Foundation of China (project Nos. 72101124), Humanities and Social Science Fund of Ministry of Education of China (project no. 20YJC630002), the China Postdoctoral Science Foundation (project Nos. 2020T130318 and 2019M661000), the Liberal Arts Development Fund of Nankai University (project No. ZX20210067).

International Journal of Contemporary Hospitality Management
Vol. 34 No. 10, 2022
pp. 3634-3654

0959-6119
DOI 10.1108/IJCHM-10-2021-1275

interaction, guests run the risk of encountering untrustworthy hosts (Jiang and Wen, 2020; Yan *et al.*, 2021). Trust plays an essential role in the process of booking accommodation, given that it creates a bond between guests and hosts who are unknown to each other (Cheng *et al.*, 2019). To understand whether the host is trustworthy and reduce the risk of choosing a poor-quality homestay, potential guests usually search for various types of information (i.e. multiple cues) through P2P platforms before booking (Zhang *et al.*, 2018). These cues include star ratings, hosts' attributes and guests' comments, which help potential guests evaluate the listings and choose accommodations (Bi *et al.*, 2020; Ert *et al.*, 2016), and enhance their judgment of the host's trustworthiness, ultimately affecting the room sales of P2P platforms. It is worth noting that the actual room booking data is not publicly available on P2P platforms. Hence, scholars have used "customer review count" as an alternative measure (Zhang *et al.*, 2018; Liang *et al.*, 2019; Xu, 2020; Biswas *et al.*, 2020). Thus, this research focuses on the "customer review count," given that this is a major indication that these listings are rented to guests on P2P platforms (Biswas *et al.*, 2020; Ranjbari *et al.*, 2020).

To promote listing sales and reduce information asymmetry, P2P platforms must issue observable and credible signals to convince guests about the room and service quality of the listing (Vo *et al.*, 2020). Therefore, quality signals or listings are the main concern of guests because these can enhance potential guests' perception of hosts' trustworthiness (Zhang *et al.*, 2018). The existing research mainly divided the quality signals of listings on P2P platforms into two categories (Filieri *et al.*, 2020). Firstly, the user-generated product quality signals, such as overall rating and attribute performance (Bi *et al.*, 2019). Secondly, the product quality signals given by third-party platforms and hosts, including excellent certificates and relevant information, such as quality attributes of hosts (Xie and Mao, 2017; Qiu *et al.*, 2021) and property attributes (Yao *et al.*, 2019).

Amongst these signals, two signals worth paying attention to are the online ratings and hosts' service quality attributes because these two digital signals are obvious on the websites and are easily captured by guests, which ensure the delivery of accommodation services (Bi *et al.*, 2021; Xie and Mao, 2017). Firstly, online ratings reflect the real attitudes of previous users towards listings and services and have high reliability and credibility (Sainaghi *et al.*, 2021; Chung and Sarnikar, 2021). Many empirical studies based on the overall rating and sub-rating have shown that the ratings are positively correlated with guests' intention to book and online sales (Liang *et al.*, 2017). Secondly, understanding hosts' service quality attributes is an important way for guests to trust the hosts (Mo *et al.*, 2021). Hosts' service quality attributes show the service quality provided by the hosts, such as 90-day availability, host identity verified, host since and host listings count (Xie and Mao, 2017). These service quality attributes can directly reflect the host's commitment to the quality of homestay services (Xie and Mao, 2017; Chang and Cheng, 2022), which influence room sales (Xie and Mao, 2017). Although some studies have explored the impact of a single information signal/cue or the impacts of different cue combinations on various factors on P2P platforms (Filieri *et al.*, 2020; Xie *et al.*, 2021; Sainaghi *et al.*, 2021), it remains unclear how online ratings and hosts' service quality attributes affect sales on P2P platforms.

Based on cue consistency theory, when multiple cues are displayed simultaneously on online platforms, the effect of one cue may interact with the effects of other cues (Kao *et al.*, 2020). When multiple consistent cues are presented to consumers, the weight and role of each cue in the consumers' evaluation will be enhanced (Hu *et al.*, 2010). However, when multiple cues are inconsistent (e.g. some positive and some negative), the negative cues tend to dominate (Hu *et al.*, 2010). Arguably, when attribute performance and hosts' service quality attributes send consistent signals to guests (i.e. both positive or negative), they may reinforce each other. However, when attribute performance and hosts' service quality attributes send inconsistent signals to guests (i.e. one positive and the other negative), they may serve merely to confuse potential consumers. However, how the combination of these two kinds of cues affects Airbnb room sales is unclear.

This study explores how the combination of attribute performance and hosts' service quality attributes affects Airbnb room sales under the conditions of consistency and inconsistency. More than 9.53 million items of user-generated content (UGC) concerning 258,473 listings on Airbnb from 35 cities worldwide were analysed using a generalized linear model. This paper adds useful insights on understanding of the cue congruence (incongruence) effect on Airbnb room sales. Practically, this paper has implications for hosts, online platform managers and guests regarding how to use online strategies and promotions on the Airbnb platform.

2. Literature review and hypothesis development

2.1 Quality signals of listings on peer-to-peer platforms

Filieri *et al.* (2020) proposed that the product quality signals on P2P platforms include the following two complementary groups: firstly, the product quality signals generated by users, such as overall rating and attribute performance, host-guest interactions, value co-creation and guest experience (Lajante *et al.*, 2022); secondly, the product quality signals given by the third-party platforms and hosts, including excellent certificates and relevant information, such as quality attributes of hosts, property attributes, hosts' self-description, price, room pictures, host photos, extra charges, region competitiveness and house rules (Ert *et al.*, 2016; Yao *et al.*, 2019; Kwok and Xie, 2019; Liang *et al.*, 2021; Kim *et al.*, 2021). Amongst these signals, two signals worth paying attention to are the online ratings and hosts' service quality attributes because these two digital signals are obvious on the websites and are easily captured by guests, which ensure the delivery of accommodation services (Xie and Mao, 2017; Assaker, 2020).

The above research helps understand the quality signals of listings. Many literatures have analysed the impact of a single cue/signal (Ert *et al.*, 2016; Liang *et al.*, 2017) or the impacts of different cues or signals on guests of electronic word-of-mouth, revenue, price or sales (Filieri, 2015; Abrate and Viglia, 2019). Some studies (Xu *et al.*, 2021) constructed a comprehensive framework to study information disclosure. Most of the studies on the influences of cues were analysed separately. Some studies have explored the interactions of multiple cues (Filieri, 2015; Sainaghi *et al.*, 2021; Yao *et al.*, 2019). For example, Filieri *et al.* (2020) verified the interactions of extremely negative ratings and product quality signals on the usefulness of reviews on the basis of negative bias and signal theory. Xie *et al.* (2021) studied the moderating effect of host type (professional and non-professional) on the relationship between guests' evaluation and listing performance.

Although these studies have attempted to investigate the impact of a single information signal/cue or the impacts of different cue combinations on various factors on P2P platforms (Xie and Mao, 2017; Filieri *et al.*, 2020; Xie *et al.*, 2021; Sainaghi *et al.*, 2021), no comprehensive picture is provided regarding the influences of online ratings and hosts' service quality attributes on sales and why these different signals have varying effects. To bridge this gap, this study explores the influence mechanisms of different cue combinations (++, −, −+, +−) of attribute performance and host attributes on sales of P2P platforms based on Airbnb evidence. Specifically, it contributes to the systematic analysis of consumer choices faced with different signals. This approach has never been implemented on P2P platforms.

2.2 Theoretical background

To bridge the gaps, this study explains the impacts of multiple inconsistent cues on sales on the basis of three theoretical backgrounds, namely, cue consistency theory (Miyazaki *et al.*, 2005), signal theory (Spence, 1973) and justice-based theory (Brockner and Wiesenfeld, 1996). Each theory has its own insights from a different angle.

2.2.1 Cue consistency theory. Cue consistency theory develops hypotheses about how consumers react to multiple cues in decision-making. Drawing on this theory, when consumers encounter multiple information sources, they may jointly assess the information (Miyazaki *et al.*, 2005) and the weight and role of each cue in consumer evaluation will be enhanced, thus promoting consumers' judgments of products or services (Hu *et al.*, 2010). Therefore, when the signals provided by two cues are consistent, a synergy exists between these cues. However, when multiple cues are inconsistent (e.g. some positive and some negative), the negative cues tend to dominate consumers' evaluation (Hu *et al.*, 2010).

2.2.2 Signal theory. We use signal theory to explain the quality signals of listings. Signal theory holds that signals are observable and changeable and can be used by individuals and organisations to communicate (Spence, 1973). In the sharing economy, multiple types of information released by-products, service providers and platforms are regarded by consumers as such signals. Filieri (2020) proposed that the product quality signals on the P2P platforms include the following two complementary groups: firstly, the product quality signals generated by users, which are measured by online ratings and reviews; secondly, the product quality signals given by the third-party platforms, including excellent certificates and relevant information (Viglia *et al.*, 2016). This study focuses on the effects of multiple combinations of these two product quality signals (ratings and hosts' service quality attributes) on sales.

2.2.3 Justice-based theory. Justice-based theories draw on justice theories (Brockner and Wiesenfeld, 1996) to explain how perceived betrayal can help understand consumer retaliation (Gregoire and Fisher, 2008). Perceived betrayal refers to the degree to which consumers feel cheated or betrayed when they believe that suppliers deliberately violate the relationships and key expectations they have established (Gregoire and Fisher, 2008). Based on justice-based theories, love can be turned into hate (Brockner and Wiesenfeld, 1996; Gregoire and Fisher, 2008). Potential guests' perceptions of inconsistent cues affect the degree to which potential guests feel betrayed by the homestays.

2.3 Conceptual background and hypothesis development

As discussed above, attribute performance and hosts' service quality attributes (i.e. "has availability," "host identity verified," "host since" and "host listings count") can be regarded as two kinds of important signals reflecting trust in Airbnb. Attribute performance indicates former guests' satisfaction with the homestay on the six attributes, reflecting service quality (Zhu *et al.*, 2020). High attribute performance indicates effective operation, which can boost online bookings (Zhu *et al.*, 2020). The higher the star ratings on these six attributes, the better the performance of these attributes and the more positive the signal these attributes send to potential guests.

Hosts' service quality attributes refer to the signals released by the hosts or third-party platforms, which reflect the service quality of the hosts (Xie and Mao, 2017). The main hosts' service quality attributes of the hosts are "has availability," "host identity verified," "host since" and "host listings count" (Xie and Mao, 2017). These attributes affect Airbnb room sales.

"Has availability" refers to whether a listing is available on particular dates (Kwok and Xie, 2019) "Host identity verified" indicates the host's identity information, such as email address and phone number, which has been verified by Airbnb. This verification process proves the legitimacy of the host, which may enhance the perceived trust of potential guests, leading to more bookings (Xie and Mao, 2017). "Host since" is expressed as the number of years the host has been operating on Airbnb. Based on learning theory, a host who has run a homestay business for a long time is expected to have a better working knowledge of the business, and therefore, can offer a smoother operating process (Liu *et al.*, 2015). The expectation is that the longer the host's operating experience (in years) is, the higher the quality of service will be, the greater the customer satisfaction and the higher the number of future bookings (Xie and Mao, 2017). In economic activities, quality and quantity are usually considered to be in conflict (Ellway, 2014). In the Airbnb context, as the "host listings count" increases (i.e. the host manages more accommodations), the expected quality of each listing will decline (Xie and Mao, 2017). Single-unit hosts may perform better than multi-unit hosts. Single-unit hosts may be more focused on managing their listing, providing high-quality service and building close relationships with their guests, which may increase their income. However, multi-unit hosts are less likely to have the energy to interact with their guests.

Generally, attribute performance and hosts' service quality attributes are two important sets of cues for potential guests to perceive the trustworthiness of the hosts. Attribute performance and hosts' service quality attributes affect Airbnb room sales. Based on cue consistency theory, this study proposes a conceptual model for testing how the combination of attribute performance and hosts' service quality attributes affects Airbnb room sales (Figure 1). Based on Figure 1, the hypothetical development of this study is given below.

Online suppliers can use cues with various assurance features to send trustworthy signals to potential customers. Based on cue consistency theory, consistent cues with positive signals can provide confirmatory information; thus, reducing the perceived risk of online consumers. In other words, when multiple cues give consistent signals, they may be used jointly by customers (Miyazaki *et al.*, 2005). Consequently, we hypothesise the following:

H1. When attribute performance and hosts' service quality attributes give positive signals, Airbnb room sales are significantly higher than when both types of cues give negative signals.

Further, negative bias suggests that consumers perceive negative cues as being more prominent, powerful and dominant in combinations and generally more effective than positive cues (Rozin and Royzman, 2001). When the two kinds of cues conflict, i.e. one set of cues gives a positive signal, and the other gives a negative signal, the negative set of cues

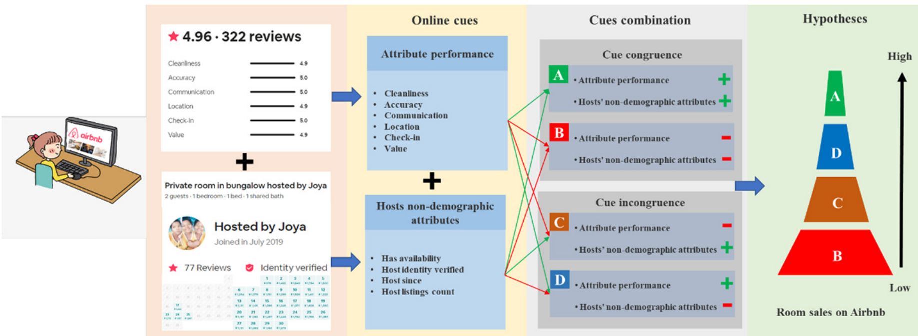

Figure 1.
Conceptual model

will compel guests to doubt the quality of the homestay, thereby reducing room sales. Conversely, when these two kinds of cues give positive signals, the weight and role of each kind of cue in guests' evaluation will be enhanced (Miyazaki *et al.*, 2005). Therefore, we hypothesise that:

H2. When attribute performance and hosts' service quality attributes give positive signals, Airbnb room sales are significantly higher than when the attribute performance and hosts' service quality attributes give inconsistent signals.

Cue consistency manipulates salience. When both kinds of cues give negative signals, the two sets of cues strengthen each other, which, in turn, convinces guests more that the quality of homestays is inferior, thereby reducing room sales. Resultantly, guests may have more confidence in their judgments on the poor-quality of homestays than when the two sets of cues are inconsistent (i.e. one giving a positive signal and one giving a negative signal). Hence, we hypothesise:

H3a. When attribute performance and hosts' service quality attributes give negative signals, Airbnb room sales will be lower than when attribute performance gives positive signals and hosts' service quality attributes give negative signals.

H3b. When attribute performance and hosts' service quality attributes give negative signals, Airbnb room sales will be lower than when attribute performance gives negative signals and hosts' service quality attributes give positive signals.

However, some scholars have different views on this. For instance, Miyazaki *et al.* (2005) found that when the two cues were inconsistent, the higher/stronger cues may not improve the customers' overall quality evaluations of the products. That is, based on previous research, the sales were similar (maybe low or higher) when the two cues gave negative signals and when the two cues were inconsistent. Thus, when both cues give negative signals, Airbnb room sales may be higher than when the two cues are inconsistent. Corresponding to *H3a* and *H3b*, the following two opposite hypotheses are further proposed:

H3c. When attribute performance and hosts' service quality attributes give negative signals, Airbnb room sales will be higher than when attribute performance gives positive signals and hosts' service quality attributes give negative signals.

H3d. When attribute performance and hosts' service quality attributes give negative signals, Airbnb room sales will be higher than when attribute performance gives negative signals and hosts' service quality attributes give positive signals.

Previous studies have examined how consumers respond to multiple inconsistent quality signals. However, the results remain ambiguous. Miyazaki *et al.* (2005) proposed that when the cues were consistent, the linear form of information integration explained the evaluation, but when the cues were inconsistent, the negative bias dominated the evaluation and the negative cues were given more weight. Similarly, Filieri *et al.* (2020) have proved that extremely negative ratings play particular roles in the decisions of TripAdvisor guests. In this study, when the two types of cues give inconsistent signals, they can be further divided into two scenarios:

(1) attribute performance gives positive signals, and hosts' service quality attributes give negative signals; or

(2) attribute performance gives negative signals, and hosts' service quality attributes give positive signals.

In these two scenarios, directly judging in which scenario sales will be higher is difficult.

Therefore, the following hypotheses are proposed:

H4a. When attribute performance gives positive signals, and hosts' service quality attributes give negative signals, Airbnb room sales are higher than when hosts' service quality attributes give positive signals and attribute performance gives negative signals.

H4b. When attribute performance gives positive signals, and hosts' service quality attributes give negative signals, Airbnb room sales are lower than when hosts' service quality attributes give positive signals and attribute performance gives negative signals.

3. Methodology

3.1 Sample and data collection

To empirically test the above hypotheses, more than 10.419 million reviews concerning 339,600 listings located in 35 major cities around the world were collected from Airbnb. As the largest P2P platform, Airbnb allows hosts to provide low-cost accommodation and enables guests to directly engage with the local communities (Xie and Mao, 2017). The time span of the collected data is from December 2019 to December 2020. These cities are Cape Town, Bangkok, Singapore, Beijing, Shanghai, Hong Kong, WA, Melbourne, Chicago, Sydney, Auckland, Amsterdam, San Francisco, Vienna, Barcelona, Berlin, Brussels, Copenhagen, Paris, Prague, Istanbul, Madrid, Los Angeles, Florence, Rome, Milan, London, Toronto, Quebec, Ottawa, New York, Mexico, Buenos Aires, Rio de Janeiro and San Diego. Because we focus on the impacts of attribute performance and hosts' service quality attributes on room sales on Airbnb, the data that did not contain these two categories of information were deleted. This left more than 9.53 million reviews concerning 258,473 listings for analysis.

The main reasons for choosing homestays in these 35 cities as the research objects are as follows:

- most of these cities are national capitals or international tourist destinations, and high vacation demands have promoted the development of homestays; and
- these cities, as international metropolises, attract tourists from all over the world, which ensures the cultural diversity of tourists and hosts, thereby reducing the influence of cultural background on the choice of homestays.

3.2 Variables

3.2.1 Main variables. There are two main types of variables involved in this study: attribute performance and hosts' service quality attributes. Specifically, on the one hand, the ratings for the six specific attributes of rooms on Airbnb (i.e. accuracy, cleanliness, check-in, communication, location and value) can be regarded as performances on the six attributes. Each attribute performance is represented as an integer ranging from 1 to 10, where 1 and 10 indicate that guests are very dissatisfied and satisfied with each attribute of the homestay in general.

On the other hand, hosts' service quality attributes in this study include four variables: "has availability," "host identity verified," "host since," and "host listings count." "Host since" is expressed as the number of years the host has operated on Airbnb; more years of operation suggests a higher quality of service (Xie and Mao, 2017). "Host listings count" referred to the number of properties owned by hosts and offered on Airbnb; here, a higher listings count is associated with a lower expectation of service quality (Xie and Mao, 2017). "Has availability" refers to whether a property is available on particular dates (Kwok and Xie, 2019). "Host identity verified" acts as a signal of quality and trust because there can be a problem with fake hosts. Thus, if the room is available for more time, the host's identity information has been verified, the host's time on Airbnb is longer and the host's listings count is low, potential guests will perceive that the host is more reliable, that is, under these situations, the hosts' service quality attributes send positive signals to guests and vice versa. "Has availability" and "host identity verified" are dummy variables, given a value of 1 when they apply and 0 otherwise. "Host since," which represents the host's length of experience with Airbnb, is calculated by deducting the start time of business from 2020. "Host listings count" refers to the number of properties owned by hosts and offered on Airbnb.

3.2.2 Dependent variable. A guest's probability of posting a review on Airbnb can be considered stable across listings (Ye *et al.*, 2009). Then, the number of reviews for a listing can be regarded as a linear function of room sales on Airbnb. Therefore, following Ye *et al.* (2009) and Biswas *et al.* (2020), the "customer review count" is used as a surrogate measure of room sales in this study – the dependent variable.

3.2.3 Control variables. Based on the previous literature, three types of variables that may affect room sales and possibly confound the results are controlled: the characteristics of homestays, language styles of guests' text comments and macro variables. Firstly, research shows that the characteristics of homestays affect their sales, so a set of these is included as control variables: room type, accommodation, number of bedrooms, number of beds and price.

Secondly, because the text comments contain the guest's evaluation information on the homestay or the host, they may affect room sales (Zhu *et al.*, 2020; Qiu *et al.*, 2022). We use the language style of these text comments to control for this. Language style refers to readability, analytical thinking, perspective-taking and sentiment orientation (Zhang *et al.*, 2020), all of which can reflect the personality and psychological needs of the tourists. Specifically, the Gunning Fog Index was calculated to estimate the readability of each comment (Goes *et al.*, 2014). The estimation formula for the Gunning Fog Index is as follows:

$$\text{Gunning Fog Index} = 0.4 \times \frac{\text{Words}}{\text{Sentences}} + 100 \times \frac{\text{Complex woods}}{\text{Woods}} \tag{1}$$

Analytical thinking is also used to measure the credibility of reviews. Based on guests' experience with homestays, the ratings given by guests with highly analytical thinking are more likely to be close to their consumption sentiment (Zhu *et al.*, 2020). Following Pennebaker *et al.* (2014), analytical thinking is calculated by equation (2):

$$\begin{aligned}\text{Analytical Thinking} = {} & 30 + \text{Article} + \text{Preposition} - \text{PersonalPronoun} \\ & - \text{ImpersonalPronoun} - \text{AuxiliaryVerb} - \text{Conjuction} \\ & - \text{Adverb} - \text{Negation}\end{aligned} \tag{2}$$

Perspective-taking refers to the process by which an individual views a thing from the perspective of another individual, which indicates a person's ability to understand and adopt another individual's psychological experience (Gerace *et al.*, 2013). Following Pennebaker *et al.* (2003), the perspective-taking is calculated by equation (3):

$$\text{Perspective} - \text{Taking} = \frac{\text{2nd Person Pronouns}}{\text{1st Person Pronouns} + \text{2nd Person Pronouns} + 0.0001} \tag{3}$$

Sentiment orientation indicates the guest's positive or negative attitude towards the homestay or the host. To measure guests' sentiment, a lexicon-based sentiment classification method is adopted in this study (Taboada *et al.*, 2011).

Finally, to avoid the influences of the development levels of different regions on room sales, we have further controlled two macro variables, i.e. the per capita GDP of the city where the homestay is located and the per capita GDP of the country where the guest came from World Bank (2020). To avoid the problem of multicollinearity, we normalize all nonbinary data into *z*-score representations.

3.3 Statistical analysis

Before conducting the empirical analysis, we conducted a test for normal distributions of the independent variables. The absolute skewness and kurtosis values for the six independent variables are all above 3, and the significance levels of the six variables are all 0.00. These results show that the independent variables do not follow a normal distribution, which makes the traditional linear regression not suitable for analysing the data. To get more reasonable analysis results, the generalized linear regression model, a model that is very suitable for analysing non-normally distributed data (Axelsen and Swan, 2010), is used in this study.

Additionally, to avoid the masking effects of multiple interaction items in a model and any potential multicollinearity effect (Way *et al.*, 2019), the impacts on room sales of performance on each attribute were separately calculated (i.e. the ratings for accuracy, cleanliness, check-in, communication, location and value). The statistical software package provided by R language software was used to estimate the results.

4. Results

Based on the above variable settings, the generalized linear regression was applied to the collected data. Tables 1, 2, 3 and 4, respectively, represent the results with respect to the cues "attribute performance and has availability," the cues "attribute performance and host identity verified," the cues "attribute performance and host since" and the cues "attribute performance and host listings count."

It can be seen from Table 1 that the coefficients of the interaction terms between "has availability" and "attribute performance" (i.e. the ratings for the six specific attributes) are all positive and at the significance level of 0.01. Similarly, it can be seen from Tables 2 and 3 that the results of the cues "host identity verified" and "host since" are consistent with those of the cue "has availability." In other words, "has availability × attribute performance," "host identity verified × attribute performance," and "host since × attribute performance" all have a significant positive impact on room sales. On the contrary, as can be seen from Table 4, the coefficients of the interaction terms between "host listings count" and "attribute performances" are

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	−0.459***	−0.443***	−0.443***	−0.442***	−0.447***	−0.443***
Has_availability	0.434***	0.434***	0.434***	0.433***	0.438***	0.434***
Accuracy	0.007***					
Cleanliness		0.004***				
Check-in			0.003***			
Communication				0.006***		
Location					0.005***	
Value						0.001***
GDP	0.011***	0.013***	0.010***	0.010***	0.011***	0.013***
Readability	0.040***	0.036***	0.038***	0.041***	0.036***	0.038***
Positive_sentiment	0.048***	0.049***	0.053***	0.052***	0.051***	0.050***
Negative_sentiment	−0.007***	−0.003	−0.005*	−0.006**	−0.003	−0.003
Analytical_thinking	0.041***	0.043***	0.040***	0.040***	0.042***	0.043***
Perspective_taking	0.007***	0.007***	0.007**	0.007**	0.009***	0.007**
Room_type	0.010***	0.008***	0.005*	0.007**	0.010***	0.003
Accommodates	0.112***	0.110***	0.110***	0.111***	0.108***	0.110***
Number_of_bedrooms	−0.144***	−0.144***	−0.145***	−0.144***	−0.144***	−0.144***
Number_of_beds	0.025***	0.025***	0.024***	0.024***	0.025***	0.025***
Price	−0.013***	−0.012***	−0.013***	−0.012***	−0.013***	−0.012***
Has_availability × Accuracy	0.085***					
Has_availability × Cleanliness		0.077***				
Has_availability × Check-in			0.082***			
Has_availability × Communication				0.076***		
Has_availability × Location					0.083***	
Has_availability × Value						0.072***

Notes: $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$

Table 1. Results of generalized linear regression analyses (attribute performance and has availability)

all negative and at the significance levels of 0.01, that is, "host listings count × attribute performance" has a significant negative impact on room sales.

Additionally, the main effects of attribute performance on room sales are all positive. Therefore, "has availability," "host identity verified" and "host since" have positive moderating effects on the relationship between attribute performance and room sales. "Host listings count" has negative moderating effects on the link between attribute performance and room sales.

To show more intuitively the influences of "attribute performance" and "hosts' service quality attributes" on room sales, the interaction plots with respect to "has availability × attribute performance," "host identity verified × attribute performance," "host since × attribute performance," and "host listings count × attribute performance" are shown, respectively, in Figures 2–5. The horizontal axis of these figures represents attribute performance, and "accuracy," "cleanliness," "check-in," "communication," "location" and "value" are, respectively, plotted in parts "a" to "f" in each figure. The vertical axis of these figures represents room sales. These figures show how room sales on Airbnb change when "attribute performance" and "hosts' service quality attributes" give different signals, where the light blue line (–) and the light red line (–) indicate that the hosts' service quality attributes give positive and negative signals, respectively.

In each of the sub-figures in Figures 2–5, the room sales corresponding to Point A are higher than the room sales corresponding to Point B. In other words, when both attribute performance and hosts' service quality attributes give positive signals, room sales on

Table 2. Results of generalized linear regression analyses (attribute performance and host identity verified)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	−0.198***	−0.198***	−0.199***	−0.199***	−0.196***	−0.199***
Host_identity_verified	0.222***	0.223***	0.224***	0.224***	0.221***	0.224***
Accuracy	0.053***					
Cleanliness		0.050***				
Check-in			0.048***			
Communication				0.043***		
Location					0.046***	
Value						0.046***
GDP	0.009***	0.011***	0.008***	0.008***	0.009***	0.010***
Readability	0.040***	0.035***	0.037***	0.040***	0.035***	0.037***
Positive_sentiment	0.045***	0.046***	0.050***	0.049***	0.048***	0.047***
Negative_sentiment	−0.007**	−0.002	−0.004*	−0.005*	−0.002	−0.002
Analytical_thinking	0.044***	0.047***	0.043***	0.043***	0.045***	0.046***
Perspective_taking	0.007***	0.007***	0.007**	0.007**	0.009***	0.007**
Room_type	0.014***	0.012***	0.010***	0.011***	0.015***	0.008***
Accommodates	0.105***	0.102***	0.103***	0.103***	0.101***	0.103***
Number_of_bedrooms	−0.141***	−0.141***	−0.142***	−0.141***	−0.140***	−0.141***
Number_of_beds	0.028***	0.027***	0.027***	0.027***	0.027***	0.028***
Price	−0.012***	−0.011***	−0.012***	−0.012***	−0.013***	−0.012***
Host_identity_verified × Accuracy	0.047***					
Host_identity_verified × Cleanliness		0.037***				
Host_identity_verified × Check-in			0.046***			
Host_identity_verified × Communication				0.048***		
Host_identity_verified × Location					0.050***	
Host_identity_verified × Value						0.033***

Notes: *p <0.10; **p <0.05; ***p <0.01

Airbnb are significantly higher than when both types of cues give negative signals. Thus, *H1* is supported.

In each of the sub-figures in Figures 2–5, the room sales corresponding to point A are higher than the room sales corresponding to point C and point D. In other words when both attribute performance and hosts' service quality attributes give positive signals, the room sales are significantly higher than when the two kinds of cues show inconsistent signals. Thus, *H2* is supported.

In each of the sub-figures in Figures 2–5, the room sales corresponding to Point B are higher than the sales corresponding to Point C, but the sales corresponding to Point B are lower than the sales corresponding to Point D. When attribute performance and hosts' service quality attributes give negative signals, the room sales are lower than when attribute performance gives positive signals and hosts' service quality attributes give negative signals, but higher than when hosts' service quality attributes give positive signals and attribute performance gives negative signals. Thus, *H3a* and *H3d* are supported, but *H3b* and *H3c* are rejected. The reason why *H3b* and *H3c* are rejected can be explained by the justice-based theory (Brockner and Wiesenfeld, 1996). From the viewpoint of justice-based theory, love can turn into hate (Gregoire and Fisher, 2008). Hosts' service quality attributes can be regarded as a promise made by hosts to users. When a host's service quality attributes give positive signals (i.e. the host's service quality is high), but attribute performance gives negative signals, it means that the host's promise to the guests has not been fulfilled. Potential guests may perceive deception and betrayal, which in turn leads to

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	-0.013^{***}	-0.012^{***}	-0.013^{***}	-0.013^{***}	-0.011^{***}	-0.012^{***}
Host since	0.133^{***}	0.134^{***}	0.132^{***}	0.131^{***}	0.135^{***}	0.135^{***}
Accuracy	0.093^{***}					
Cleanliness		0.083^{***}				
Check-in			0.086^{***}			
Communication				0.082^{***}		
Location					0.093^{***}	
Value						0.075^{***}
GDP	0.000	0.003	0.000	0.000	0.002	0.002
Readability	0.017^{***}	0.013^{***}	0.015^{***}	0.018^{***}	0.013^{***}	0.015^{***}
Positive_sentiment	0.043^{***}	0.043^{***}	0.048^{***}	0.047^{***}	0.045^{***}	0.044^{***}
Negative_sentiment	-0.008^{***}	-0.005^{*}	-0.006^{**}	-0.006^{**}	-0.003^{*}	-0.005^{*}
Analytical_thinking	0.041^{***}	0.043^{***}	0.040^{***}	0.040^{***}	0.042^{***}	0.042^{***}
Perspective_taking	0.009^{***}	0.009^{***}	0.009^{***}	0.009^{***}	0.011^{***}	0.009^{***}
Room_type	0.016^{***}	0.015^{***}	0.012^{***}	0.014^{***}	0.018^{***}	0.010^{***}
Accommodates	0.117^{***}	0.115^{***}	0.115^{***}	0.115^{***}	0.113^{***}	0.115^{***}
Number_of_bedrooms	-0.147^{***}	-0.146^{***}	-0.148^{***}	-0.147^{***}	-0.146^{***}	-0.147^{***}
Number_of_beds	0.027^{***}	0.026^{***}	0.026^{***}	0.026^{***}	0.027^{***}	0.027^{***}
Price	-0.013^{***}	-0.012^{***}	-0.012^{***}	-0.012^{***}	-0.013^{***}	-0.012^{***}
Host since × Accuracy	0.025^{***}					
Host since × Cleanliness		0.021^{***}				
Host since × Check-in			0.026^{***}			
Host since × Communication				0.024^{***}		
Host since × Location					0.035^{***}	
Host since × Value						0.020^{***}

Notes: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 3. Results of generalized linear regression analyses (attribute performance and host since)

lower sales. Hosts' service quality attributes can be regarded as a promise made by hosts to users. When hosts' service quality attributes give positive signals (i.e. the hosts' service quality is high), but attribute performance gives negative signals, this shows that the host's promise to the guests has not been fulfilled. Potential guests may be given a feeling of deception and betrayal, which, in turn, leads to lower sales.

Furthermore, based on *H3a* and *H3d*, the results show that when attribute performance and hosts' service quality attributes give negative signals, Airbnb room sales are lower than when attribute performance gives positive signals, and hosts' service quality attributes give negative signals, but higher than when attribute performance gives negative signals and hosts' service quality attributes give positive signals. The reason why the negative effect of attribute performance is larger than that of hosts' service quality attributes can be explained by the nature of cues. Newman *et al.* (2016) pointed out that cues can be classified as evaluative or objective. Evaluation cues are based on a personal evaluation of the personal impression made by the whole product or specific product attributes and are a form of explanatory information (Darley and Smith, 1993). Accordingly, attribute performance on Airbnb can be regarded as evaluative cues because they represent evaluations of and explanatory information about homestays provided by other guests. One of the key characteristics of objective cues is the degree of factual information provided (Darley and Smith, 1993). Therefore, hosts' service quality attributes are objective cues in that they present factual information that has been verified by the Airbnb platform. These cues are designed to help Airbnb guests evaluate homestays effortlessly and quickly by reducing the

Table 4. Results of generalized linear regression analyses (attribute performance and host listings count)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	−0.011***	−0.011***	−0.011***	−0.011***	−0.010***	−0.011***
Host_listings_count	−0.056***	−0.056***	−0.056***	−0.056***	−0.058***	−0.057***
Accuracy	0.089***					
Cleanliness		0.079***				
Check-in			0.084***			
Communication				0.079***		
Location					0.087***	
Value						0.069***
GDP	0.012***	0.015***	0.011***	0.011***	0.013***	0.014***
Readability	0.039***	0.035***	0.037***	0.039***	0.035***	0.037***
Positive_sentiment	0.049***	0.050***	0.053***	0.052***	0.051***	0.051***
Negative_sentiment	−0.007***	−0.003	−0.005*	−0.006**	−0.003	−0.003
Analytical_thinking	0.039***	0.041***	0.038***	0.039***	0.040***	0.041***
Perspective_taking	0.007***	0.007**	0.007**	0.007**	0.008***	0.007**
Room_type	0.005*	0.003	0.001	0.002	0.006**	−0.001
Accommodates	0.113***	0.111***	0.111***	0.111***	0.109***	0.111***
Number_of_bedrooms	−0.143***	−0.142***	−0.144***	−0.143***	−0.142***	−0.143***
Number_of_beds	0.025***	0.024***	0.024***	0.024 ***	0.025***	0.025***
Price	−0.013***	−0.013***	−0.013***	−0.013***	−0.014***	−0.013***
Host_listings_count × Accuracy	−0.009***					
Host_listings_count × Cleanliness		−0.008***				
Host_listings_count × Check-in			−0.009***			
Host_listings_count × Communication				−0.008***		
Host_listings_count × Location					−0.009***	
Host_listings_count × Value						−0.007***

Notes: $^{*}p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$

cognitive burden of cue interpretation and utilisation (Feunekes *et al.*, 2008). Evaluation cues have stronger effects than objective cues because the latter usually lack specific explanatory components (Newman *et al.*, 2016). When facing evaluative and objective cues, the former has greater impact on potential guests' decisions. Therefore, the negative signal of attribute performance is more powerful than the hosts' service quality attributes.

In each of the sub-figures in Figures 2–5, the room sales corresponding to Point D are higher than the room sales corresponding to Point C. When attribute performance gives positive signals, and hosts' service quality attributes give negative signals, room sales are higher than when hosts' service quality attributes give positive signals and attribute performance gives negative signals. Thus, *H4a* is supported, but *H4b* is rejected. As mentioned above, attribute performance signals are evaluative cues, whereas hosts' service quality attributes are objective cues. If either attribute performance or hosts' service quality attributes give negative signals, whereas the other offer positive signals, negative signals from attribute performance will convince guests more that the quality of the homestay is worse than negative signals from hosts' service quality attributes, which in turn means that room sales will be less in the former circumstance.

5. Discussion and conclusions

5.1 Conclusions

This study explored how the combination of attribute performance and hosts' service quality attributes affects Airbnb room sales under the conditions of consistency and inconsistency by using more than 9.53 million items of UGC concerning 258,473 Airbnb

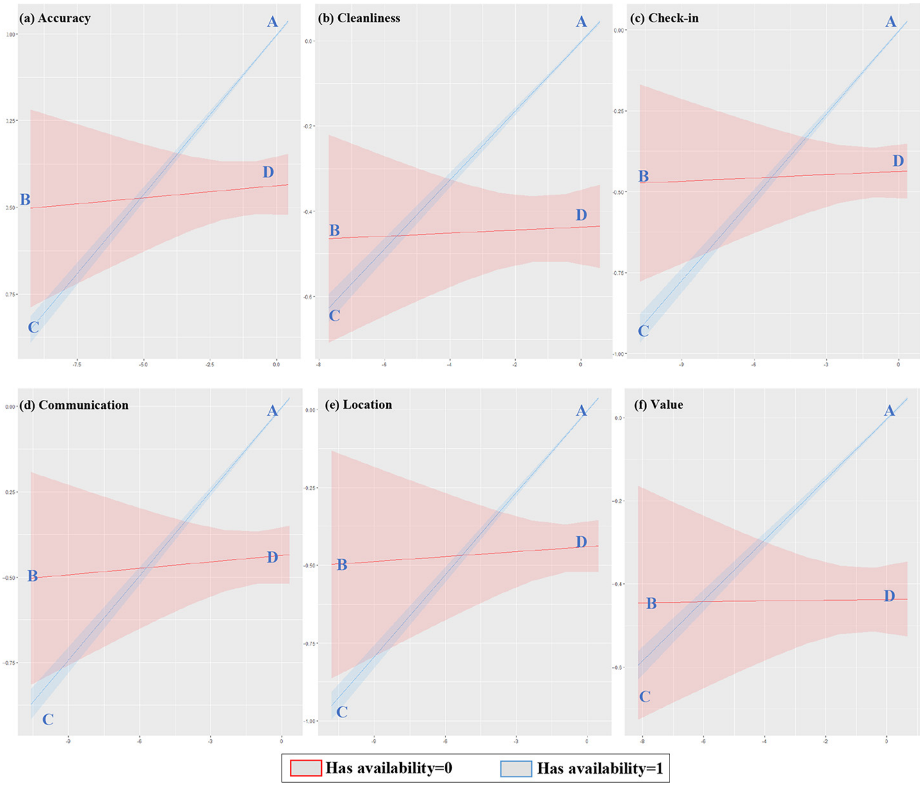

Figure 2.
The effects of the combination of "has availability" and "attribute performance" on room sales

listings for accommodation in 35 major cities worldwide. The results show, firstly, when attribute performance and hosts' service quality attributes give positive signals, Airbnb room sales are significantly higher than when the two sets of cues give inconsistent signals. Secondly, when both sets give positive signals, Airbnb room sales are significantly higher than when both sets of cues give negative signals. Thirdly, when attribute performance gives positive signals and hosts' service quality attributes give negative signals, Airbnb room sales are higher than when hosts' service quality attributes give positive signals and attribute performance gives negative signals. Fourthly, surprisingly, when attribute performance and hosts' service quality attributes give negative signals, Airbnb room sales are higher than when attribute performance gives positive signals and hosts' service quality attributes give negative signals. This research provides theoretical and practical insights into several areas.

5.2 Theoretical implications

The current study findings yield three important theoretical implications. This study has advanced theoretical knowledge of signal theory (Spence, 1973) and cue consistency theory (Hu *et al.*, 2010). Although previous studies have attempted to investigate the impact of a single information signal/cue or the impacts of different cue combinations on various factors on P2P platforms (Xie and Mao, 2017; Filieri *et al.*, 2020; Xie *et al.*, 2021; Sainaghi *et al.*, 2021),

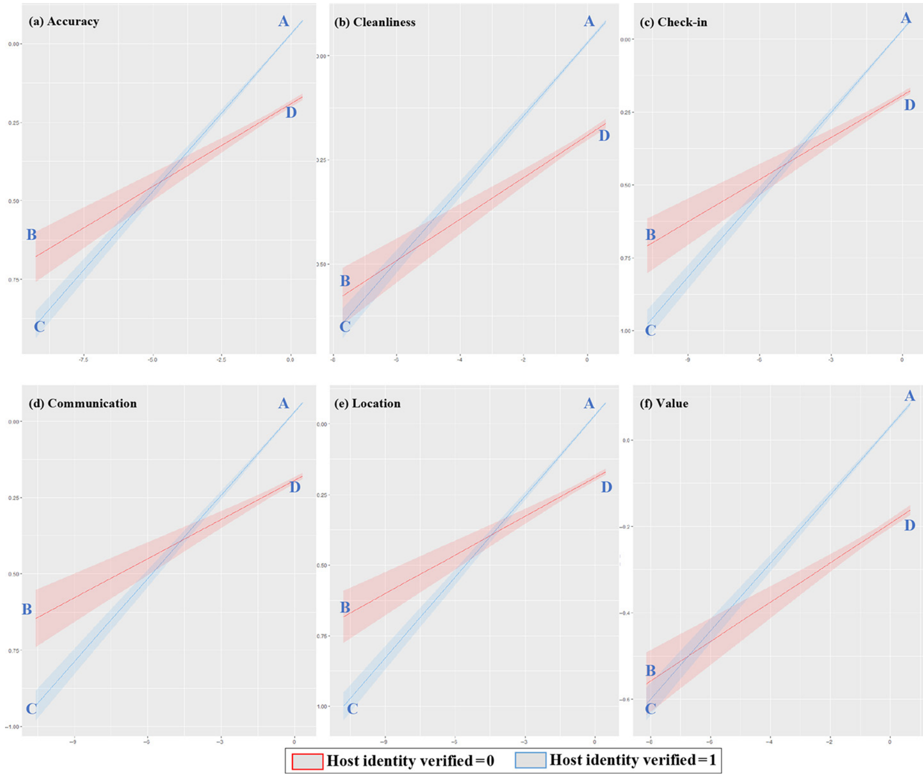

Figure 3.
The effects of the combination of "host identity verified" and "attribute performance" on room sales

no comprehensive picture is provided regarding the influences of online ratings and hosts' service quality attributes on P2P platform sales, and why these different signals have varied effects. The current study combined cue consistency theory and signal theory to explore the influences of signals from a more comprehensive perspective. The results (*H1* and *H2*) reveal that when attribute performance and hosts' service quality attributes give positive signals, Airbnb room sales are significantly higher than when both types of cues give negative signals or give inconsistent signals. By testing the joint effects of attribute performance and hosts' service quality attributes on sales, this study helps advance the literature on the interaction effects of different signals and cues.

H3 implies that when attribute performance and hosts' service quality attributes give negative signals, Airbnb room sales will be lower (higher) than when they give inconsistent signals. However, the results are not entirely in line with these expectations. Specifically, when attribute performance and hosts' service quality attributes give negative signals, room sales are lower than when attribute performance gives positive signals and hosts' service quality attributes give negative signals, but higher than when hosts' service quality attributes give positive signals and attribute performance gives negative signals (*H3a* and *H3d*). These counterintuitive results can be explained by the justice-based theory. When a host's service quality attributes give positive signals, it means that the host has established bonds and promises with the guest. Then, when attribute performance is lower than

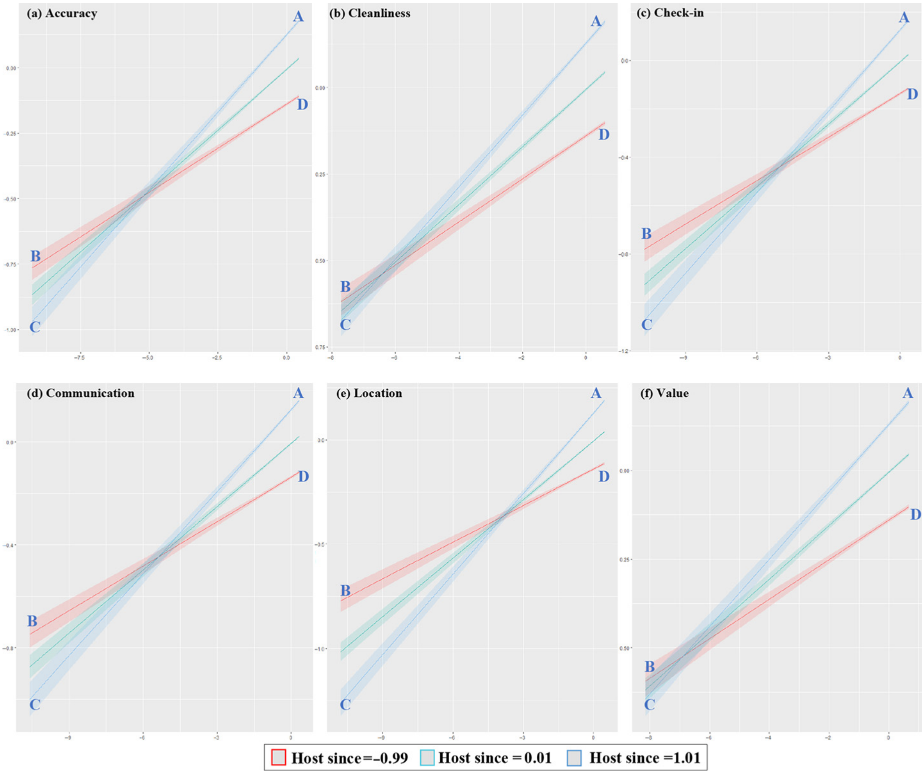

Figure 4.
The effects of the combination of "host since" and "attribute performance" on room sales

expected, the guest will feel deceived and betrayed, which will result in guests' retaliatory behaviour and lead to a significant drop in sales.

Furthermore, the results (*H3d* and *H4*) further reveal that when attribute performance and hosts' service quality attributes give different signals, guests pay more attention to attribute performance than hosts' service quality attributes. Although previous research has proved that extremely negative ratings play particular roles in guests' decision-making on TripAdvisor (Filieri *et al.*, 2020), these studies have not thoroughly explained this phenomenon. This study classified cues as either evaluative or objective, according to Newman *et al.* (2016). Therefore, attribute performance on Airbnb has been regarded as evaluative cues, whereas hosts' service quality attributes are objective cues. When attribute performance and hosts' service quality attributes give different signals, guests pay more attention to evaluative cues than objective cues (Darley and Smith, 1993). The results help clarify the decision-making mechanism when guests encounter consistent or inconsistent cues when booking homestays.

5.3 Practical implications

This study has three practical implications for hosts, P2P platform managers and guests. Firstly, as an evaluative cue, attribute performance plays a greater role in consumer decision-making than hosts' service quality attributes. Therefore, hosts must focus on improving the attribute performance and encourage guests to give high ratings on the six

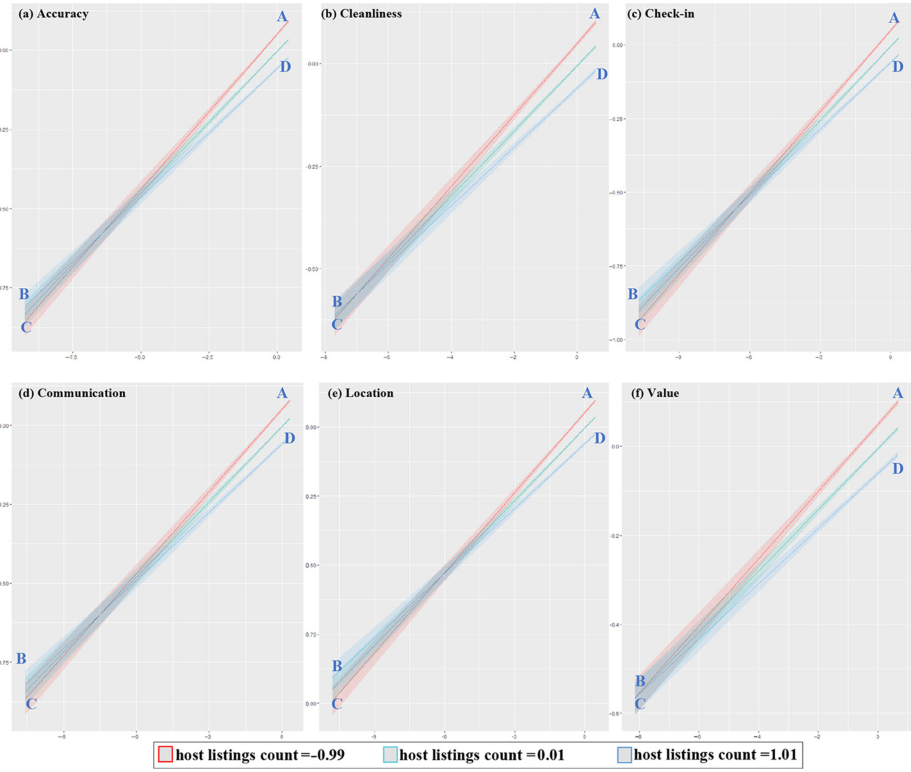

Figure 5.
The effects of the combination of "host listings count" and "attribute performance" on room sales

attributes-perhaps through rewards or other means. Moreover, when attribute performance is high, if the host's service quality attributes can send positive signals to potential guests, the host should actively disclose information, such as the listing available time is longer, the host identity has been verified by the platform, the host has a long operating time and the listing count operated by the host is small. Counterintuitively, however, when attribute performance is low, even if the host's service quality attributes would normally send positive signals to guests, the host should reduce the disclosure of this information. Platform-certified hosts must strive to maintain the same (high) quality standards to avoid gaps between the service quality expected by consumers and the actual service quality.

Secondly, P2P platform managers must encourage hosts to disclose information and expand the channels to verify hosts' information in various ways. Firstly, platform managers can, directly and indirectly, promote and regulate information disclosure of hosts and guests. The platforms can encourage hosts to post text descriptions, pictures, ratings, demo videos and other forms of information to help guests fully understand the listings and services. Secondly, platform managers must expand the channels to verify the hosts, which can show the platforms' intention to regulate, monitor and control the hosts and the transactions, provide consumers with the sense of security they expect from the platforms and generate purchase behaviours.

Third, guests must not only pay attention to a single aspect of information but must also pay attention to multiple aspects of the information provided by the P2P platforms, especially ratings.

Guests must also pay attention to hosts' information and certifications, compare these signals with ratings and check the consistency of multiple signals for ideal decision-making.

5.4 Limitations and further research

The current study has certain limitations, which deserve future research attention. Firstly, due to data limitations, this study only explored four aspects of hosts' service quality attributes, namely, "has availability," "host identity verified," "host since" and "host listings count". More aspects must be explored in future research. Secondly, consumer experience and cultural background may influence consumers' booking decisions. Future studies could explore whether these factors affect the impacts of multiple cues on Airbnb room sales. Thirdly, the sample of this study is limited to Airbnb, and future research can be tested on Meituan, TripAdvisor and other platforms. Fourthly, the differences between attribute performance and hosts' service quality attributes hold many reasons, including not only trust but possibly different data sources (marketer-generated content and UGC), as well as sources that influence guests' perceived value. Future studies can further explore the influencing factors that lead to inconsistent cues. Fifthly, this research had to use the "count of customer reviews" as a surrogate measure of room sales because the actual booking data is not publicly available. Future studies can be tested with more accurate data. Sixthly, some control variables can be further considered, including the reviewers' characteristics and the review time.

References

Abrate, G. and Viglia, G. (2019), "Personal or product reputation? Optimizing revenues in the sharing economy", *Journal of Travel Research*, Vol. 58 No. 1, pp. 136-148.

Assaker, G. (2020), "The effects of hotel green business practices on consumers' loyalty intentions: an expanded multidimensional service model in the upscale segment", *International Journal of Contemporary Hospitality Management*, Vol. 32 No. 12, pp. 3787-3807.

Axelsen, M. and Swan, T. (2010), "Designing festival experiences to influence visitor perceptions: the case of a wine and food festival", *Journal of Travel Research*, Vol. 49 No. 4, pp. 436-450.

Bi, J.W., Li, H. and Fan, Z.P. (2021), "Tourism demand forecasting with time series imaging: a deep learning model", *Annals of Tourism Research*, Vol. 90 No. 103255.

Bi, J.W., Liu, Y. and Li, H. (2020), "Daily tourism volume forecasting for tourist attractions", *Annals of Tourism Research*, Vol. 83 No. 102923.

Bi, J.W., Liu, Y., Fan, Z.P. and Zhang, J. (2019), "Wisdom of crowds: conducting importance performance analysis (IPA) through online reviews", *Tourism Management*, Vol. 70, pp. 460-478.

Biswas, B., Sengupta, P. and Chatterjee, D. (2020), "Examining the determinants of the count of customer reviews in peer-to-peer home-sharing platforms using clustering and count regression techniques", *Decision Support Systems*, Vol. 135, p. 113324.

Brockner, J. and Wiesenfeld, B.M. (1996), "An integrative framework for explaining reactions to decisions: interactive effects of outcomes and procedures", *Psychological Bulletin*, Vol. 120 No. 2, pp. 189-208.

Chang, Y.-Y. and Cheng, C.-C. (2022), "New insights into the measurement model of a new scale for evaluating restaurant service quality during major infectious disease outbreaks", *International Journal of Contemporary Hospitality Management*, Vol. 34 No. 5, pp. 1629-1648.

Cheng, X., Fu, S., Sun, J., Bilgihan, A. and Okumus, F. (2019), "An investigation on online reviews in sharing economy driven hospitality platforms: a viewpoint of trust", *Tourism Management*, Vol. 71, pp. 366-377.

Chung, Y. and Sarnikar, S. (2021), "Understanding host marketing strategies on Airbnb and their impact on listing performance: a text analytics approach", *Information Technology and People*, doi: 10.1108/ITP-10-2020-0718.

Darley, W.K. and Smith, R.E. (1993), "Advertising claim objectivity: antecedents and effects", *Journal of Marketing*, Vol. 57 No. 4, pp. 100-113.

De Canio, F., Nieto-García, M., Martinelli, E. and Pellegrini, D. (2020), "The motives behind consumers' intention to use peer-to-peer accommodation: an fsQCA application", *International Journal of Contemporary Hospitality Management*, Vol. 32 No. 9, pp. 2969-2989.

Ellway, B.P.W. (2014), "Is the quantity-quality trade-off in call centers a false dichotomy",? *Managing Service Quality*, Vol. 24 No. 3, pp. 230-251.

Ert, E., Fleischer, A. and Magen, N. (2016), "Trust and reputation in the sharing economy: the role of personal photos in Airbnb", *Tourism Management*, Vol. 55, pp. 62-73.

Feunekes, G., Gortemaker, I.A., Willems, A.A., Lion, R. and Kommer, M. (2008), "Front-of-pack nutrition labelling: testing effectiveness of different nutrition labelling formats front-of-pack in four European countries", *Appetite*, Vol. 50 No. 1, pp. 57-70.

Filieri, R. (2015), "What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM", *Journal of Business Research*, Vol. 68 No. 6, pp. 1261-1270.

Filieri, R., Vitari, C. and Raguseo, E. (2020), "Extreme negative rating and review helpfulness: the moderating role of product quality signals", *Journal of Travel Research*, Vol. 60 No. 4, pp. 699-717.

Gerace, A., Day, A., Casey, S. and Mohr, P. (2013), "An exploratory investigation of the process of perspective taking in interpersonal situations", *Journal of Relationships Research*, Vol. 4, pp. 1-12.

Goes, P.B., Lin, M. and Au Yeung, C.M. (2014), "Popularity effect in user-generated content: evidence from online product reviews", *Information Systems Research*, Vol. 25 No. 2, pp. 222-238.

Gregoire, Y. and Fisher, R.J. (2008), "Customer betrayal and retaliation: when your best customers become your worst enemies", *Journal of the Academy of Marketing Science*, Vol. 36 No. 2, pp. 247-261.

Hu, X., Wu, G., Wu, Y. and Han, Z. (2010), "The effects of web assurance seals on consumers' initial trust in an online vendor: a functional perspective", *Decision Support Systems*, Vol. 48 No. 2, pp. 407-418.

Jiang, Y. and Wen, J. (2020), "Effects of COVID-19 on hotel marketing and management: a perspective article", *International Journal of Contemporary Hospitality Management*, Vol. 32 No. 8, pp. 2563-2573.

Kao, K.C., Rao, H.S. and Troshani, I. (2020), "Effects of cue congruence and perceived cue authenticity in online group buying", *Internet Research*, Vol. 30 No. 3, pp. 945-970.

Kim, S.I., Kim, J., Koh, Y. and Bowen, J.T. (2021), "Toward maximization of peer-to-peer accommodation hosts' competitive productivity (CP)", *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 9, pp. 3003-3020.

Kwok, L. and Xie, K.L. (2019), "Pricing strategies on Airbnb: are multi-unit hosts revenue pros"?, *International Journal of Hospitality Management*, Vol. 82, pp. 252-259.

Lajante, M., Ladhari, R. and Massa, E. (2022), "Role of affective forecasting in customers' hotel service experiences", *International Journal of Contemporary Hospitality Management*, Vol. 34 No. 3, pp. 1062-1083.

Liang, S., Schuckert, M., Law, R. and Chen, C. (2017), "Be a 'superhost': the importance of badge systems for peer-to-peer rental accommodations", *Tourism Management*, Vol. 60, pp. 454-465.

Liang, S., Schuckert, M., Law, R. and Chen, C.C. (2019), "The importance of marketer-generated content to peer-to-peer property rental platforms: evidence from Airbnb", *International Journal of Hospitality Management*, Vol. 84 No. 102329.

Liang, S., Zhang, X., Li, C., Li, H. and Yu, X. (2021), "Tit for tat: understanding the responding behavior of property hosts on peer-to-peer rental platforms", *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 3, pp. 1105-1126.

Liu, X., Wright, M. and Filatotchev, I. (2015), "Learning, firm age and performance: an investigation of returnee entrepreneurs in Chinese high-tech industries", *International Small Business Journal: Researching Entrepreneurship*, Vol. 33 No. 5, pp. 467-487.

Miyazaki, A., Grewal, D. and Goodstein, R.C. (2005), "The effect of multiple extrinsic cues on quality perceptions: a matter of consistency", *Journal of Consumer Research*, Vol. 32 No. 1, pp. 146-153.

Mo, Z., Liu, M.T. and Wong, I.A. (2021), "More than lip service to internal market orientation: a multilevel investigation of the role of internal service quality", *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 8, pp. 2559-2585.

Newman, C.L., Howlett, E. and Burton, S. (2016), "Effects of objective and evaluative front-of-package cues on food evaluation and choice: the moderating influence of comparative and noncomparative processing contexts", *Journal of Consumer Research*, Vol. 42 No. 5, pp. 749-766.

Pennebaker, J.W., Mehl, M.R. and Niederhoffer, K.G. (2003), "Psychological aspects of natural language use: our words, our selves", *Annual Review of Psychology*, Vol. 54 No. 1, pp. 547-577.

Pennebaker, J.W., Chung, C.K., Frazee, J., Lavergne, G.M. and Beaver, D.I. (2014), "When small words foretell academic success: the case of college admissions essays", *PLoS One*, Vol. 9 No. 12, p. e115844.

Qiu, H., Chen, D., Bi, J.-W., Lyu, J. and Li, Q. (2022), "The construction of the affinity-seeking strategies of Airbnb homestay hosts", *International Journal of Contemporary Hospitality Management*, Vol. 34 No. 3, pp. 861-884.

Qiu, H., Chen, D., Lyu, J., He, H. and Li, C. (2021), "Affinity-seeking strategies of homestay hosts: scale development and validation", *Journal of Hospitality and Tourism Management*, Vol. 49, pp. 195-203.

Ranjbari, M., Shams Esfandabadi, Z. and Scagnelli, S.D. (2020), "A big data approach to map the service quality of short-stay accommodation sharing", *International Journal of Contemporary Hospitality Management*, Vol. 32 No. 8, pp. 2575-2592.

Rozin, P. and Royzman, E.B. (2001), "Negativity bias, negativity dominance, and contagion", *Personality and Social Psychology Review*, Vol. 5 No. 4, pp. 296-320.

Sainaghi, R., Abrate, G. and Mauri, A. (2021), "Price and RevPAR determinants of Airbnb listings: convergent and divergent evidence", *International Journal of Hospitality Management*, Vol. 92 No. 102709.

Spence, M. (1973), "Job market signaling", *The Quarterly Journal of Economics*, Vol. 87 No. 3, pp. 355-374.

Taboada, M., Brooke, J., Tofiloski, M., Voll, K.D. and Stede, M. (2011), "Lexicon-based methods for sentiment analysis", *Computational Linguistics*, Vol. 37 No. 2, pp. 267-307.

Viglia, G., Minazzi, R. and Buhalis, D. (2016), "The influence of E-Word-of-Mouth on hotel occupancy rate", *International Journal of Contemporary Hospitality Management*, Vol. 28 No. 9, pp. 2035-2051.

Vo, N.T., Chovancová, M. and Tri, H.T. (2020), "The impact of E-service quality on the customer satisfaction and consumer engagement behaviours toward luxury hotels", *Journal of Quality Assurance in Hospitality and Tourism*, Vol. 21 No. 5, pp. 499-523.

Way, K., Jimmieson, N.L. and Bordia, P. (2019), "Supervisor conflict management climate and emotion recognition skills: implications for collective employee burnout", *International Journal of Conflict Management*, Vol. 31 No. 4, pp. 559-580.

World Bank (2020), "World development indicators", available at: https://data.worldbank.org/indicator/NY.GDP.PCAP.CD

Xie, K. and Mao, Z. (2017), "The impacts of quality attributes of Airbnb hosts on listing performance", *International Journal of Contemporary Hospitality Management*, Vol. 29 No. 9, pp. 2240-2260.

Xie, K., Heo, C.Y. and Mao, Z.E. (2021), "Do professional hosts matter? Evidence from multi-listing and full-time hosts in Airbnb", *Journal of Hospitality and Tourism Management*, Vol. 47, pp. 413-421.

Xu, X. (2020), "How do consumers in the sharing economy value sharing? Evidence from online reviews", *Decision Support Systems*, Vol. 128.

Xu, X., Zeng, S. and He, Y. (2021), "The impact of information disclosure on consumer purchase behavior on sharing economy platform Airbnb", *International Journal of Production Economics*, Vol. 231 No. 107846.

Yan, R., Zhang, K.Z. and Gong, X. (2021), "Listing popularity on the peer-to-peer accommodation platform: the heuristic-systematic and uncertainty reduction perspectives", *International Journal of Contemporary Hospitality Management*, Vol. 33 No. 12, pp. 4161-4181.

Yao, B., Qiu, R.T.R., Fan, D.X.F., Liu, A. and Buhalis, D. (2019), "Standing out from the crowd – an exploration of signal attributes of Airbnb listings", *International Journal of Contemporary Hospitality Management*, Vol. 31 No. 12, pp. 4520-4542.

Ye, Q., Law, R. and Gu, B. (2009), "The impact of online user reviews on hotel room sales", *International Journal of Hospitality Management*, Vol. 28 No. 1, pp. 180-182.

Zhang, L., Yan, Q. and Zhang, L. (2018), "A computational framework for understanding antecedents of guests' perceived trust towards hosts on Airbnb", *Decision Support Systems*, Vol. 115, pp. 105-116.

Zhang, L., Yan, Q. and Zhang, L. (2020), "A text analytics framework for understanding the relationships among host self-description, trust perception and purchase behavior on Airbnb", *Decision Support Systems*, Vol. 133 No. 113288.

Zhu, L., Lin, Y. and Cheng, M. (2020), "Sentiment and guest satisfaction with peer-to-peer accommodation: when are online ratings more trustworthy"?, *International Journal of Hospitality Management*, Vol. 86 No. 102369.

Corresponding author
Jian-Wu Bi can be contacted at: jianwubi@126.com