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Sentiment and guest satisfaction with peer-to-peer accommodation: When are online ratings more trustworthy?

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ABSTRACT

This study aims to decode guest satisfaction with peer-to-peer accommodations by analyzing the relationship between guests' sentiment and online ratings and examining how analytical thinking and authenticity influence this relationship. Based on reviews of 4602 Airbnb listings in San Francisco, we empirically find that positive (negative) sentiment is linked to a high (low) rating. We further show that this link is stronger when guests manifest a higher extent of analytical thinking and authenticity. Both Tobit and ordered logit models yield consistent estimation results, showing the robustness of our findings. Our study contributes to the tourism and hospitality literature by theoretically explaining the association between sentiment and ratings. In addition, this paper enriches our knowledge regarding the trustworthiness of Airbnb ratings.

1. Introduction

The past decade has witnessed the rapid growth and increasing popularity of the sharing economy (Cheng, 2016), which has disrupted many industries, including lodging services (Birinci et al., 2018). As one of the Silicon Valley success stories, Airbnb innovatively provides guests with "atypical accommodations" that make them feel at home (Liu and Mattila, 2017; Zhu et al., 2019). This platform has topped many old players in the lodging industry and has been the most influential pioneer of peer-to-peer (P2P) accommodation platforms since its launch in 2008. In 2018, Airbnb has 4.5 million listings in over 190 countries and 300 million guests (Airbnb, 2018).

Like traditional accommodation providers, Airbnb and its hosts must keep satisfying their guests, as evidence shows that high customer satisfaction can lead to the success of accommodation businesses (Radojevic et al., 2015). While many hotels still rely on questionnaires to gauge customer satisfaction, the recent emergence of online review services represents a frontier in decoding customer satisfaction (Radojevic et al., 2017). Online reviews greatly benefit the lodging industry, including P2P accommodations. On the one hand, the ratings in an online review system reflect the extent of guest satisfaction with accommodations; on the other hand, review comments unveil guests' feelings, attitudes and evaluations. Airbnb uses a reciprocal online review system to build trust between guests and hosts and monitor guest satisfaction (Ert et al., 2016; Guttentag, 2015). This review system presents detailed ratings and review comments by guests, and it helps Airbnb and hosts identify and understand guests' needs and consequently provide better services to improve guest satisfaction.

High ratings not only signal effective operation and management but also facilitate favorable word of mouth to boost online accommodation bookings (Ye et al., 2011), as guests regard ratings and reviews as important information sources in lodging decision making. It is important for hosts to understand how a guest arrives at a certain rating and what aspects should be accordingly improved. Researchers and practitioners have specified and emphasized many determinants of accommodation ratings, such as accommodation rankings, costs, amenities, and service quality as well as guests' power distance (Gao et al., 2018; Heras-Saizarbitoria et al., 2015; Radojevic et al., 2015, 2017). Textual reviews in combination with ratings can also help hosts identify the causes of certain ratings. Researchers have hypothesized that a link exists between reviews and ratings (e.g., sentiment scores and ratings) but largely failed to provide a theoretical explanation for such a link. More importantly, some embedded features of review comments have been ignored.

In this study, we focus on sentiment embedded in textual reviews. Consumption emotions are key elements of guests' responses that affect customer satisfaction, especially in the lodging industry (Han and Back, 2006, 2007). The actual sentiment that guests express through online reviews aptly captures their consumption emotions. As highlighted by Geetha et al. (2017), there is a need to understand the association

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between this sentiment and guests' ratings. Guests' sentiment related to their consumption emotion should serve as a solid base for their satisfaction with P2P accommodations, thus affecting their rating behavior. Nonetheless, researchers and business journalists have noticed an extraordinarily positive skew in Airbnb review ratings, raising concerns regarding the trustworthiness of the ratings (Bridges and Vsquez, 2016; Fradkin et al., 2015a,b; Ho, 2015; Zervas et al., 2015). Therefore, it is appealing to investigate when online ratings truly reflect the sentiment of guests, or when online ratings are more trustworthy.

In this paper, we conduct text analysis to investigate guests' reviews of Airbnb listings in San Francisco. Specifically, the Linguistic Inquiry and Word Count (LIWC) program is employed to extract the sentiment of guests to discuss the link between sentiment and review ratings and identify guests' ability and willingness to provide ratings that are more trustworthy.

2. Literature review

2.1. Guest satisfaction with accommodations

Customer satisfaction is one of the most researched areas in service management, including hospitality and tourism. Customer satisfaction plays a central role in customers' post-purchase behavior, including return intention and positive word of mouth (Ahrholdt et al., 2017; HennigThurau and Klee, 1998). Despite the novel experiences offered by peer-to-peer accommodations, insufficient attention is paid to guests' satisfaction with these accommodations (Priporas et al., 2017a; Tussyadiah, 2016).

In the very few studies investigating guests' satisfaction with P2P accommodations, researchers have explored the determinants of satisfaction in rather limited ways. Table 1 presents recent studies on P2P satisfaction. These various studies largely measure satisfaction using a survey-based approach. Thus, the respondents self-report their satisfaction upon request. With the popularity of review ratings, scholars argue that online ratings and reviews provide a more naturalist and reflective evaluation of guest satisfaction (Wu and Pearce, 2014; Xiang et al., 2015). Scholars have suggested that guests' ratings reflect customer satisfaction, a central concept in marketing research, rather than product quality (Engler et al., 2015; Yi, 1990). Consequently, research in different domains, such as movies (Moon et al., 2010), hotels (Guo et al., 2017) and video games (Liu et al., 2015), is increasingly employing online ratings to analyze satisfaction.

Compared with customer satisfaction data collected by traditional surveys, online ratings data are more reliable and valid in predicting accommodation performance (Kim and Park, 2017). Review ratings not only provide valuable feedback to managers but also act as recommendations for future customers and affect the reputation of accommodations (Radojevic et al., 2015). For example, by linking Airbnb guest reviews and online ratings, Tussyadiah and Zach (2017) show that Airbnb users who express that they "feel welcome" are likely to be more satisfied and give higher rating scores.

However, explorations that link key attributes to online ratings ignore sentiment, which is an essential dimension of review comments, even though its importance has been highlighted in the hotel and restaurant literature (Lee et al., 2017). For example, Gan et al. (2016) demonstrate that customers' sentiment in relation to five attributes of restaurant service performance has significant impacts on restaurants' star ratings. Similarly, Geetha et al. (2017) show that customer sentiment polarity explains the significant variation in customer ratings across different hotel categories. Bridges and Vásquez (2016) call for more research to go beyond merely focusing on ratings and to consider Airbnb guests' constructions of their experiences in review comments, particularly focusing on their style of communication. It thus makes sense to elucidate the link between sentiment in review comments and guests' ratings to decode guest satisfaction with Airbnb listings.

2.2. Sentiment analysis

Sentiment analysis has become popular with the explosion of unstructured textual information available on the Internet. Using statistical and computational algorithms, sentiment analysis is a process of identifying and classifying subjective opinions/attitudes (positive, neutral or negative) toward a certain topic in the text.

Two main approaches have been frequently used in sentiment analysis: the machine-learning approach and the lexicon-based approach (Liu, 2010). The former involves building statistical classifiers from text that have been previously labeled (i.e., positive or negative). The classifier is used to predict the sentiment of unlabeled text (Pang et al., 2002). In contrast, the latter uses dictionaries of words and phrases (e.g., adjectives) that have been annotated with the word's semantic orientation (i.e., positive or negative) to calculate the sentiment of the text (Taboada et al., 2011; Turney, 2002).

The machine-learning approach requires time and effort to manually label the text, and it relies heavily on the quality of the training data and model; thus, this approach may suffer from over-fitting and weak generalizability of the trained model (Medhat et al., 2014). In comparison, the lexicon-based approach is more efficient. A well-defined lexicon can be sufficiently accurate and readily used in real-time applications (Chaovalit and Zhou, 2005; Pang and Lee, 2008). In this paper, we adopt the latter approach, which can be performed using various software programs, such as LIWC and SentiWordNet. A detailed explanation of the mainstream algorithms and their applicability, as well as various software programs, can be found in the work of Ma et al. (2018).

In tourism and hospitality, sentiment analysis helps businesses not only measure tourists' or guests' attitudes toward their products and services but also position themselves in the market with competitors (Ma et al., 2018). A recent review of sentiment analysis in tourism and hospitality indicates that most studies end at the sentiment classification level without linking sentiment to other important variables for more advanced analysis (Geetha et al., 2017; Ma et al., 2018). Only in the last few years have studies started to bridge this gap. For example,

Table 1
Key determinants of guests' satisfaction with Airbnb accommodations.

Authors	Determinants	Methods (data collection)
Mohlmann (2015)	Utility, trust, cost savings, and familiarity	Survey Self-reported satisfaction
Tussyadiah (2016)	Enjoyment, monetary benefits (value), accommodation, and amenities	Survey Self-reported satisfaction
Priporas et al. (2017a)	Service quality (25 items from Akbaba (2006))	Survey Self-reported satisfaction
Tussyadiah and Zach (2017)	"Feeling at home"	Online review comments and ratings
S. Lee and Kim (2018)	Airbnb users' hedonic and utilitarian value. Product involvement plays a moderating role in the paths between hedonic value and customer satisfaction.	Survey Self-reported satisfaction

by integrating Service Quality (SEVQUAl) models, Liu et al. (2013) analyze the sentiment of tourists toward key hotel service quality attributes. Mao et al. (2018) reveal that sentiment scores reflect an accurate evaluation of each aspect of the sleeping environment in a hotel setting.

The rich information imbedded in textual reviews, including guests' sentiment, can be extracted by sentiment analysis. This enables an empirical test of the link between sentiment and rating scores, which helps us further decode guests' satisfaction with P2P accommodations. To add to the increasing body of research investigating sentiment and P2P accommodations, this study not only reinforces the link between sentiment and guests' ratings in the Airbnb context but also examines when this relationship is stronger and guests' ratings are more trustworthy.

3. Conceptual model and hypothesis development

3.1. Sentiment and online ratings

Geetha et al. (2017) attempted to investigate the relationship between guests' ratings and review sentiment in tourism and hospitality. While their study empirically tests this relationship in the traditional hotel domain, they fail to provide a theoretical argument for this relationship. The theoretical link between guests' ratings and review sentiment is rooted in the research on emotion and customer satisfaction. Research on emotion considers emotional state as an important cognitive process that arises from appraisals of events or thoughts (Bagozzi and Nataraajan, 2000; Schachter and Singer, 1962). Since guests' ratings represent customer satisfaction in the Airbnb context, they are likely affected by guests' emotions, which have been well documented as a key driver of satisfaction. For instance, Chang (2008) suggests that consumption emotions are a set of emotional responses induced by consumption experiences and notes that these emotional responses are strongly linked to customer satisfaction.

Sentiment refers to a cognitively motivated and rationalized expression of social disposition (Dragouni et al., 2016). It has been described as the attitude toward particular events or situations following cognitive involvement and the cognitive schema determining people's perception (Frijda, 1986, 1994). Therefore, sentiment shares many common features with emotion. Indeed, sentiment and emotion analysis are considered the same in prior studies, and the two terms are used interchangeably (Gopaldas, 2014; Rout et al., 2018; Wang et al., 2016). Since emotions have been reported to affect customer satisfaction, a relation between sentiment and customer satisfaction can also be expected.

Appraisal theorists maintain that emotions are triggered by the evaluation and interpretation that follow the comparison of actual and desired states (Roseman, 1991). The link between consumption emotions and satisfaction is thus easy to see, as satisfaction is regarded as a post-consumption cognitive process in which customers compare the perceived performance of a service with their expectations (Westbrook and Oliver, 1991). Additionally, satisfaction has been demonstrated to incorporate emotional responses elicited during consumption (Roest and Pieters, 1997; Westbrook, 1987). Similar to consumption emotion, sentiment relates to the way customers evaluate services (Dragouni et al., 2016). Sentiment about peer-to-peer accommodations is determined by guests' experiences with these accommodations. Guests' sentiment reflects their opinion, attitude, evaluation, and emotions related to the services offered by hosts. Hence, sentiment is connected to guest satisfaction, proxied by online ratings. Specifically, guests' positive (vs. negative) sentiment toward P2P accommodations comes from their pleasant (vs. unpleasant) experiences, leading to higher (vs. lower) rating scores of accommodations. We accordingly posit the following hypotheses:

H1a. Positive sentiment toward P2P accommodations is associated with an increase in online ratings.

H1b. Negative sentiment toward P2P accommodations is associated with a decrease in online ratings.

3.2. Trustworthiness of the sentiment-rating link

Sentiment toward P2P accommodations is an indicator of guest satisfaction and relates to guests' online ratings. However, the relationship between sentiment and online ratings has been challenged due to the extraordinarily positive skew of Airbnb's ratings (Bridges and Vsquez, 2016; Fradkin et al., 2015a,b; Ho, 2015; Zervas et al., 2015). In fact, whether ratings can truly reflect guests' consumption sentiment is subject to their analytical thinking style and authenticity, which affect how information is translated and incorporated into numerical ratings. While the former affects guests' ability to link ratings to their consumption sentiment, the latter reflects their willingness to express their sentiment with the corresponding ratings.

Research in the fields of cognitive and social psychology suggests that people's cognition and behavior operate in two types of thinking modes, namely, intuitive and analytical thinking (Leron and Hazzan, 2009). While intuitive thinking refers to an associative, heuristic and automatic/subconscious process, analytical thinking is rule-based, conscious, and logical (Iannello, 2009). In addition, analytical thinking implies great use of cognitive resources and requires deliberate efforts (Schroyens et al., 2003; Stanovich and West, 2001). People who rely heavily on analytical thinking pay considerable attention to formal, abstract and logical connections (Verschueren et al., 2005) and intend to make decisions with explicit bases (Iannello, 2009). In a more recent discussion by Pennebaker (2015), analytical thinking is described as a formal and hierarchical thinking pattern, and low analytical thinking is linked to a focus on the here-and-now.

Representing satisfaction, online ratings are also decisions made by guests when evaluating services in P2P accommodations. Since guests' sentiment regarding P2P accommodations is cognitively motivated and rationalized (Dragouni et al., 2016) and based on their experiences with the accommodations, guests with a high extent of analytical thinking are more able to assign ratings that are consistent with their consumption sentiment. These guests draw heavily on working memory resources (Ejersbo and Leron, 2014) and make utilitarian judgments with deliberative reasoning (Li et al., 2018). They can recall their consumption sentiment for reliable ratings. Therefore, their ratings are more trustworthy. In contrast, people with low analytical thinking make decisions effortlessly and non-consciously (Ejersbo and Leron, 2014). They are less capable of using past consumption sentiment as a solid base when providing ratings after the consumption of accommodation services. Consequently, the analytical thinking mode enhances the connection between online ratings and sentiment. More specifically, if guests rely more heavily on analytical thinking, their positive (vs. negative) sentiment is more likely to be reflected in their ratings and hence result in high (vs. low) ratings of the accommodation. We thus propose the following hypotheses exploring the moderation effect of analytical thinking:

H2a. The association between positive sentiment toward P2P accommodations and an increase in online ratings is enhanced by guests' analytical thinking.

H2b. The association between negative sentiment toward P2P accommodations and a decrease in online ratings is enhanced by guests' analytical thinking.

Even when guests have the ability to show their true feelings, they might not be willing to voice their true opinion (i.e., authenticity) in their ratings. Authenticity can be simply regarded as the consistency between thoughts/feelings and actions (Michie and Gooty, 2005). This concept implies that people express themselves in a consistent way with their inner thoughts and feelings and act in line with their true selves (Harter, 2002). Wood et al. (2008) also conclude that if people have high authenticity, their behavior and emotional expression are "consistent with the conscious awareness of physiological states, emotions, beliefs, and cognitions" (pp. 386). Therefore, it can be expected that authentic guests' ratings of Airbnb accommodations align with their opinions about the services.

Airbnb listings receive extraordinarily positive ratings and much higher average rating scores than hotels listed in TripAdvisor (Bridges and Vsquez, 2016; Zervas et al., 2017). Several factors may contribute to this positivity bias. The first one is the avoidance of a "face-threatening act", which in politeness theory means damaging the face of other people by acting against their wants and desires (Brown and Levinson, 1987). As Airbnb requests both guests and hosts to verify their personal information, the review process virtually becomes a face-to-face conversation. Moreover, since Airbnb guests are more likely to have some contact with the hosts during their stay, providing low ratings after this contact can be difficult and awkward (Bridges and Vásquez, 2016). Second, the reciprocity of Airbnb's review system could be another reason for the positivity bias of the ratings. In this system, guests expect favorable feedback and fear retaliation from hosts, and, thus, are inclined to provide hosts with high ratings (Fradkin et al., 2015a,b). For either reason, guests' reviews may not reflect their true sentiment.

However, authenticity helps minimize inconsistencies between actions and will. Authentic guests tend to act in correspondence with their internal experience and involve honesty in their outward behavior and communication (White and Tracey, 2011). Regardless of their motivations for providing certain ratings against their will, guests with high authenticity have a high intention to honestly express their opinions and rate listings in accordance with their conscious awareness of their physiological states, emotions, beliefs, and cognitions. The more authentic the guests are, the more willing they are to give trustworthy ratings that adhere to their consumption sentiment. In line with this argument, the following hypotheses are proposed to investigate the moderation effect of authenticity:

H3a. The association between positive sentiment toward P2P accommodations and the increase in online ratings is enhanced by guests' authenticity.

H3b. The association between negative sentiment toward P2P accommodations and the decrease in online ratings is enhanced by guests' authenticity.

4. Research design

4.1. Data

The data for this paper are obtained from the "Inside Airbnb" website (InsideAirbnb.com). This website is based on a data collection project that publicizes information about Airbnb's listings but is independent of Airbnb. The detailed review information from this source provides opportunities to analyze guests' comments using sentiment analysis, which facilitates further investigation of the relationship between sentiment and guests' ratings in the peer-to-peer accommodation context.

The sample employed in this study covers 4602 listings in San Francisco, where Airbnb headquarters is located. Each listing has one average rating score but displays the comments of all individual guests. To examine the link between sentiment in comments and review ratings, we aggregate the comments on listings to extract guests' sentiment toward the listings.

4.2. Variables and measures

This study aims to examine the relationship between sentiment and ratings and the trustworthiness of the ratings. The rating score of each listing (***Rating Score***), which is a proxy of guest satisfaction, is the dependent variable. The key independent variables are related to guests' sentiment and are generated by the LIWC program. This program relies on a text analysis module and a group of built-in dictionaries to process review comments. Specifically, the text analysis module compares the words used in the review comments with the words in built-in dictionaries, and it associates the words with appropriate psychologically relevant categories. The program sequentially calculates the percentage of total words that match each category. In this study, ***Positive Sentiment*** and ***Negative Sentiment*** are our key independent variables. The LIWC program counts the words reflecting positive or negative sentiment and converts the number into a percentage for each listing. Notably, some words are neutral and are included in neither a positive nor a negative category.

Likewise, the two moderators, namely, ***Analytical Thinking*** and ***Authenticity***, are generated by the LIWC program. These two summary variables are composites based on word count results. The formulas are designed by Pennebaker et al. (2015) to calculate the values of the variables. As described by Pennebaker et al. (2014), high ***Analytical Thinking*** is associated with the greater use of categorical language (i.e., greater article and proposition use), whereas low analytical thinking is associated with more dynamic language (i.e., greater use of auxiliary verbs, pronouns, adverbs, conjunctions, and negations). The formula provided in Pennebaker et al. (2014) for calculating ***Analytical Thinking*** is as follows:

$$\begin{aligned}\boldsymbol{Analytical\ Thinking} = 30 &+ \text{Article} + \text{Preposition} - \text{Personal Pronoun} \\ &- \text{Impersonal Pronoun} - \text{Auxiliary Verb} \\ &- \text{Conjunction} - \text{Adverb} - \text{Negation}\end{aligned} \tag{1}$$

where the variables on the right-hand side refer to the percentages of different function words among all words. For example, Article is the number of articles divided by the total number of words. The number 30 is added to the formula to ensure that the score is typically positive. This measure has been widely used in studies in the fields of psychology and management, such as Boyd and Pennebaker (2015); Buyl et al. (2019), and Hwong et al. (2017).

Authenticity measures the degree to which the linguistic style reflects that the author is telling the truth. Newman et al. (2003) find that liars tend to use (1) fewer self-references and other-references; (2) more negative emotion words; and (3) more cognitive complex words. These researchers use the following measurement of ***Authenticity***:

$$\boldsymbol{Authenticity} = \text{Negative Words} + \text{Cognitive Words} - \text{Self References} \tag{2}$$

where the variables on the right-hand side refer to the percentages of different types of words among all words. This measurement of ***Authenticity*** has also been used and verified in previous studies (e.g., Hobson et al., 2012; Larcker and Zakolyukina, 2012; Li, 2008).

Two sets of control variables are also taken into account to control more factors in the empirical analysis. The first set refers to service quality. As service quality has been documented as an essential driver of customer satisfaction (Caruana, 2002; Kuo et al., 2009; Priporas et al., 2017b), it is strongly linked to guests' ratings. The service quality set contains the number of accommodations offered on Airbnb by the host (***Host Listings Count***), the host's experience with serving guests (***Hosting Duration***), number of reviews, host's response speed and host's response rate. Xie and Mao (2017) argue that having more rooms listed compromises the quality of host operations; thus, the ***Host Listing Count*** is a measure of the service quality. ***Hosting Duration*** starts from the date when a listing first launches on Airbnb.com until the date when the data was scraped. A longer operation period may increase the host experience for better services, but researchers are concerned about other outcomes, such as rusting procedures and inefficient service delivery (Wirtz and Lovelock, 2016). Thus, the impact of ***Hosting Duration*** on guest satisfaction is inconclusive. A similar conclusion can be drawn for the ***Number of Reviews***. This variable indicates the number of guests served by a host and, as a result, is connected to a host's experience with providing service. Hosts can learn from serving guests and increase their service quality, but a large number of guests may cause an inferior guest focus (Fečiková, 2004) and decrease service quality. In addition, the ***Response Speed*** and ***Response Rate*** variables imply the efficiency of hosts' services and are also used to represent service quality. ***Response Speed*** is measured using a 4-point scale (4 if the host responses within an hour; 3 if within a few hours; 2 if within a day; 1 if in a few days or more).

The second set of control variables relates to renting policies. Customers appreciate convenience in purchasing and consuming products/services (Athanassopoulos, 2000; Kim et al., 2009). Renting policies may lead to convenience or inconvenience for guests, which consequently affects rating scores. Four kinds of policies are discussed in the empirical section: cancellation policy, instant book policy, profile picture requirement for guests and phone verification requirement for guests. The ***Cancellation Policy*** variable is measured using a 6-point scale (the strictness of the cancellation policy: flexible = 6; moderate = 5; strict = 4; super_strict_30[1] = 3; super_strict_60[2] = 2; no refunds = 1). The remaining three are all dummy variables. The ***Instant Book Policy*** variable equals 1 if hosts allow guests to instantly book accommodations without hosts' approval and 0 otherwise. The ***Profile Picture Requirement*** is coded as 1 when the guest is required to provide a profile picture and 0 otherwise. Similarly, for the ***Phone Verification Requirement***, 1 indicates that the guest is required to verify his/her phone number, and 0 indicates otherwise.

4.3. Estimation method

The dependent variable in this study is the ***Rating Score***, which is truncated to range between 0 (the lower limit) and 100 (the upper limit). Given the truncated property of the dependent variable, the ordinary least squares (OLS) estimation is not appropriate, as it may produce biased and inconsistent parameter estimates (Amemiya, 1984). Therefore, the Tobit model is employed to investigate the relationship between the rating scores and guests' sentiment and the moderation effects of analytical thinking and authenticity. The review score y_i can be written as follows:

$$y_i = \begin{cases} y_i^* & if\ y_L < y_i^* < y_U, \\ y_L & if\ y_i^* \le y_L, \\ y_U & if\ y_i^* \ge y_U \end{cases} \tag{3}$$

where y^* is a latent variable that linearly depends on a vector of explanatory variables $\boldsymbol{x}$ and can be written as $y^* = \boldsymbol{x}^T\boldsymbol{\beta} + \mu$; $\boldsymbol{\beta}$ is a vector of parameters to be estimated; μ captures the random unobserved factors that affect y^* and is assumed to be normally distributed; and y_L (y_U) is the lower (upper) limit and equals 0 (100) in our study.

One concern is that the ***Rating Score*** has an ordinal nature as it only reflects the relative ranking of the listings, and the actual distances between each category may not necessarily be equal (Alan, 2013). Methods based on means and standard deviations may be inappropriate for inferential statistics involving ordinal dependent variables (Stevens, 1946). To address this concern, we also estimate the ordered logit model (OLM) designed for ordinal dependent variables. Similar to the Tobit model, the OLM is based on the latent-variable equation $y^* = \boldsymbol{x}^T\boldsymbol{\beta} + \mu$ and can be written as follows (Markwat et al., 2009):

$$y = \begin{cases} 0, & if\ y^* < \alpha_1, \\ 1,\ , & if\ \alpha_1 < y^* < \alpha_2, \\ 2, & if\ \alpha_2 < y^* < \alpha_3, \\ \dots & \\ 100, & if\ \alpha_{100} < y^* \end{cases} \tag{4}$$

If we further assume that $\alpha_0 = -\infty$ and $\alpha_{101} = +\infty$, the model can be simply re-written as

$$\text{y= j if } \alpha_j < y^* < \alpha_{j+1}, \text{ for j= 0,1, ..., m}-1, \tag{5}$$

In the OLM, μ is assumed to follow a standardized logistic distribution. Using the link between y and y^* as specified above, the probability of getting a score j is given by

$$P_j = \Pr[y = j] = \quad (\alpha_{j+1} - \boldsymbol{x}^T\boldsymbol{\beta}) - \quad (\alpha_j - \boldsymbol{x}^T\boldsymbol{\beta}),\ \dots \text{ for j= 0,1, ..., m}-1 \tag{6}$$

where Λ is a logistic function, and $(\alpha_0 - \boldsymbol{x}^T\boldsymbol{\beta}) \equiv 0$ and $(\alpha_m - \boldsymbol{x}^T\boldsymbol{\beta}) \equiv 1$.

The various models are estimated by the statistical packages provided in Stata 15.

5. Findings

5.1. Descriptive statistics

Table 2 provides the descriptive statistics for all variables included in the empirical analysis. The results indicate an average satisfaction ***Rating Score*** of 95.23 (SD = 5.35). On average, guests' sentiment toward Airbnb listings is more positive than negative. The means of ***Positive Sentiment*** and ***Negative Sentiment*** are 11.07 (SD = 3.49) and 0.28 (SD = 0.31), respectively. Guests' thinking styles are relatively formal, logical, and hierarchical, as ***Analytical Thinking*** has an average value over 50 (mean = 67.10, SD = 9.55). Meanwhile, guests' comments are characterized by a guarded, distanced type of discourse, as the mean of ***Authenticity*** is below 50 (mean = 41.86, SD = 11.90) (Pennebaker et al., 2015).

As for the control variables, hosts operate more than one listing on average, with the mean of ***Host Listings Count*** being 3.80 (SD = 12.54). Hosts are very active in replying to guest queries, with high mean values of response speed (mean = 3.47, SD = 0.75) and rate (mean = 97%, SD = 0.10). On average, hosts have approximately 3–4 years of operation experience (mean = 1391.14, SD = 709.32), and the average number of reviews of listings is approximately 47 (mean = 46.90, SD = 60.97). Hosts on Airbnb set relatively moderate cancellation policies (mean = 4.59, SD = 0.70), but only 29% of them allow instant booking. Hosts rarely require guests to have a profile picture or phone verification, with mean values of 0.06 (SD = 0.24) and 0.07 (SD = 0.25), respectively.

5.2. Estimation results

The main results of the analysis are reported in Table 3. Model 1 contains only the control variables and moderators. Model 2 tests the effects of the main independent variables, namely, ***Positive Sentiment*** and ***Negative Sentiment***. Models 3 and 4 introduce moderation effects with ***Analytical Thinking*** and ***Authenticity***, respectively. Model 5 is a complete model.

The effects of sentiment are first examined in Model 2. The coefficient of ***Positive Sentiment*** is positive and significant (coeff. = 0.3072, $p < 0.001$). This indicates that a higher rating score can be expected if the guest's comment on the accommodation is more positive, providing support for H1a. In contrast, the coefficient of ***Negative Sentiment*** is significantly negative (coeff. = –4.2846, $p < 0.001$). The link between guests' negative sentiment and a decrease in rating scores is thus confirmed, and H1b is supported.

[1] Guests can receive a refund if they cancel their order 30 days before the check-in date.

[2] Guests can receive a refund if they cancel their order 60 days before the check-in date.

Table 2
Descriptive Statistics.

	Mean	S.D.	Min	Max
Rating Score	95.23	5.35	40	100
Positive Sentiment (%)	11.07	3.49	0.00	46.15
Negative Sentiment (%)	0.28	0.31	0.00	5.02
Analytic Thinking	67.10	9.55	16.35	99.00
Authenticity	41.86	11.90	0.67	99.00
Host Listing Count	3.80	12.54	0.00	248.00
Response Speed	3.47	0.75	1.00	4.00
Response Rate	0.97	0.10	0.00	1.00
Hosting Duration	1391.14	709.32	25	3500
Number of Reviews	46.90	60.97	1	542
Cancellation Policy	4.59	0.70	3.00	6.00
Instant Booking	0.29	0.46	0.00	1.00
Profile Picture Requirement	0.06	0.24	0.00	1.00
Phone Verification Requirement	0.07	0.25	0.00	1.00

moderator (i.e., ***Analytical Thinking*** and ***Authenticity***) is high or low. The blue (red) line with circle (square) markers in Fig. 1.1 shows how the ***Rating Score*** changes with ***Positive Sentiment*** when ***Analytical Thinking*** is low (high). Similarly, the blue (red) line with circle (square) markers in Fig. 1.2 shows how the ***Rating Score*** changes with ***Negative Sentiment*** when ***Analytical Thinking*** is low (high). Clearly, as shown in Fig. 1.2, the influence of ***Negative Sentiment*** on the ***Rating Score*** is stronger among people with high ***Analytical Thinking*** than that among people with low ***Analytical Thinking*** as the red line has a steeper slope than the blue line. In contrast, the difference between the slopes of the two lines in Fig. 1.1 is not apparent. This finding confirms the significant (insignificant) interaction between ***Negative*** (***Positive***) ***Sentiment*** and ***Analytical Thinking***.

Fig. 2 also shows the interaction plots based on Model 5 and provides a similar conclusion to Fig. 1. The red line in Fig. 2.2 has a steeper slope than the blue line, indicating that the impact of ***Negative Sentiment*** on the Rating Score is stronger among people with high ***Authenticity***. However, the two lines in Fig. 2.1 are almost parallel, suggesting that the impacts of ***Positive Sentiment*** on the ***Rating Score*** are almost the same among people with high and low ***Authenticity***. Therefore, the significant (insignificant) interaction between ***Negative*** (***Positive***) ***Sentiment*** and ***Authenticity*** is confirmed.

Table 3
Estimation Results (Tobit Models).

Dependent Variable: Rating Score					
	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	91.1909***	91.7110***	91.5968***	91.7954***	91.6463***
Positive Sentiment		0.3064***	0.2935***	0.2927***	0.2814***
Negative Sentiment		−4.2610***	−4.5033***	−4.0172***	−4.2638***
Positive Sentiment × Analytical Thinking			0.0035		0.0030
Negative Sentiment × Analytical Thinking			−0.0903***		−0.1146***
Positive Sentiment ×Authenticity				0.0017	0.0009
Negative Sentiment ×Authenticity				−0.0930***	−0.1111***
Moderators					
Analytical Thinking	−0.0353***	−0.0419***	−0.0420***	−0.0455***	−0.0458***
Authenticity	−0.0984***	−0.0930***	−0.0954***	−0.0925***	−0.0949***
Control Variables					
Host Listing Count	−0.0560***	−0.0602***	−0.0609***	−0.0586***	−0.0591***
Response Speed	−0.0737	−0.0874	−0.0766	−0.1006	−0.0818
Response Rate	3.7145***	3.5054***	3.5382***	3.5416***	3.6095***
Hosting Duration	0.0004**	0.0004**	0.0004**	0.0004**	0.0004**
Number of Reviews	−0.0080***	−0.0065***	−0.0064***	−0.0066***	−0.0064***
Cancellation Policy	0.3979**	0.3124*	0.3132*	0.2998*	0.2980*
Instant Book	−1.1492***	−1.1727***	−1.1650***	−1.1327***	−1.1193***
Profile Picture Requirement	−0.1787	−0.0494	−0.0816	0.0534	0.0818
Phone Verification Requirement	−0.1227	−0.0420	−0.0400	−0.0483	−0.0496
Number of Observations	4602	4602	4602	4602	4602
Log Likelihood	−12748.88	−12555.91	−12543.93	−12539.12	−12522.48
LR Chi-Squared	329.95***	715.89***	739.85***	749.47***	782.74***

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

The moderation effect of ***Analytical Thinking*** on the relationship between sentiment and rating scores is sequentially investigated. As expected, guests' analytical thinking reinforces the negative association between guests' negative sentiment and rating scores, since the interaction of ***Negative Sentiment*** and ***Analytical Thinking*** yields significantly negative coefficients in both Model 3 (coeff. = –0.0918, p < 0.001) and Model 5 (coeff. = –0.1161, p < 0.001). Nonetheless, the moderation effect is not confirmed for guests' positive sentiment as the coefficient of the interaction term (***Positive Sentiment*** × ***Analytical Thinking***) is insignificant. Therefore, this empirical study supports H2b but not H2a. Similarly, the negative coefficients for the interaction of ***Negative Sentiment*** and ***Authenticity*** are significant in both Model 4 (coeff. = –0.0939, p < 0.001) and Model 5 (coeff. = –0.1121, p < 0.001), while the moderation effect for positive sentiment cannot be proven. As a result, H3b is verified, but H3a is not.

For illustration, we provide interaction plots in accordance with Model 5 (Fig. 1.1 & Fig. 1.2). The x-axes in the two figures refer to ***Positive Sentiment*** (Fig. 1.1) and ***Negative Sentiment*** (Fig. 1.2). The y-axes represent the ***Rating Score***. The interaction plots show how the dependent variable changes as the variable of interest changes (i.e., ***Positive Sentiment*** and ***Negative Sentiment***) in different cases when the

To eliminate the concern about the ordinal nature of the dependent variable, i.e., the Rating Score, we consider the OLM as an alternative model specification. The results with OLM specification are presented in Table 4, and Models 6–10 correspond to Models 1–5 in Table 3, respectively. It is apparent that both the Tobit Model and OLM produce consistent estimation results. This consistency showcases the robustness of the results in our empirical analysis.

6. Discussion and implications

6.1. Main findings

This paper essentially reveals two sets of findings. The first focuses on the link between guests' sentiment and rating scores. According to our empirical analysis, guests with a higher extent of positive sentiment

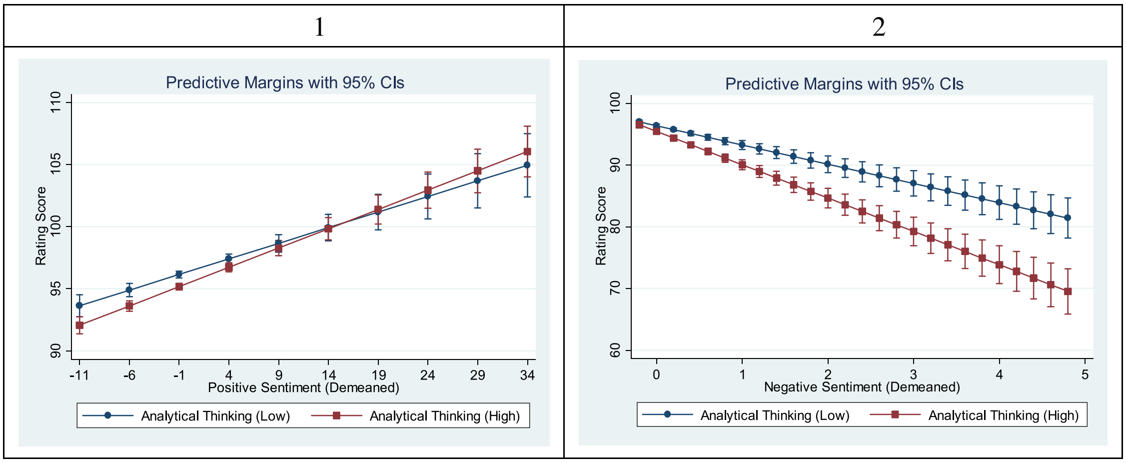

Fig. 1. Interaction Plots of Sentiments and Analytical Thinking.

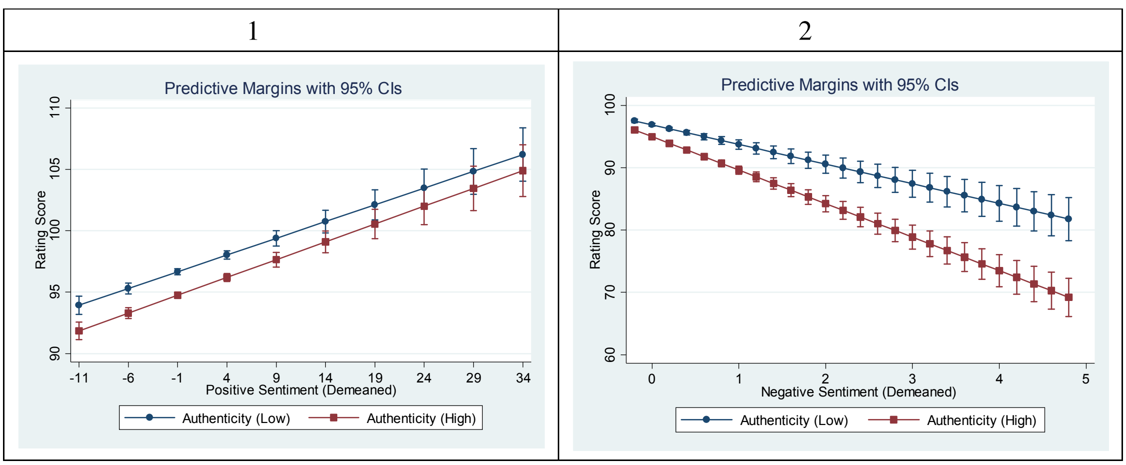

Fig. 2. Interaction Plots of Sentiments and Authenticity.

Table 4
Robustness Check (Ordered Logit Models).

Dependent Variable: Rating Scores					
	Model 6	Model 7	Model 8	Model 9	Model 10
Positive Sentiment		0.0752***	0.0737***	0.0706***	0.0694***
Negative Sentiment		−1.4034***	−1.4274***	−1.4336***	−1.4701***
Positive Sentiment × Analytical Thinking			0.0004		0.0003
Negative Sentiment × Analytical Thinking			−0.0278***		−0.0296***
Positive Sentiment ×Authenticity				0.0003	0.0002
Negative Sentiment ×Authenticity				−0.0418***	−0.0414***
Moderators					
Analytical Thinking	−0.0132***	−0.0162***	−0.0164***	−0.0172***	−0.0175***
Authenticity	−0.0317***	−0.0314***	−0.0318***	−0.0318***	−0.0321***
Control Variables					
Host Listing Count	−0.0156***	−0.0168***	−0.0170***	−0.0163***	−0.0168***
Response Speed	−0.0142	−0.0274	−0.0252	−0.0276	−0.0254
Response Rate	1.1170***	1.2317***	1.2404***	1.2415***	1.2532***
Hosting Duration	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**
Number of Reviews	−0.0034***	−0.0031***	−0.0031***	−0.0031***	−0.0031***
Cancellation Policy	0.1112**	0.1036**	0.1043**	0.0950*	0.0957*
Instant Book	−0.2716***	−0.2683***	−0.2689***	−0.2535***	−0.2529***
Profile Picture Requirement	−0.0156	0.0038	0.0024	0.0033	0.0030
Phone Verification Requirement	−0.0259	−0.0033	−0.0026	−0.0017	−0.0018
Number of Observations	4602	4602	4602	4602	4602
Log Likelihood	−11844.54	−11687.23	−11680.42	−11666.92	−11659.47
LR Chi-Squared	363.31***	677.93***	691.56***	718.55***	733.44***

Note: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

are more likely to give high rating scores for peer-to-peer accommodations, whereas guests with a higher extent of negative sentiment are more likely to act in the opposite way. Our results hence establish the link between the review text and the rating scores. In addition, the magnitude of the coefficient for the ***Negative Sentiment*** variable is much larger than that for the ***Positive Sentiment*** variable, which implies that guests are more sensitive to negative affect than to positive affect. This finding is consistent with the existing literature that illustrates the stronger impact of various negatively valenced events (e.g., negative affect and emotional distress) on individuals than positively valenced events of the same type (e.g., positive affect and pleasant emotions) (Baumeister et al., 2001). People generally pay more attention to negative information than positive information (Ito et al., 1998; Rozin and Royzman, 2001). Negative word of mouth is usually more influential than positive word of mouth (Chen et al., 2011; Chevalier and Mayzlin, 2006), and consumers consider negative reviews more useful (Kuan et al., 2015).

The second set of findings is related to the moderation effects of ***Analytical Thinking*** and ***Authenticity***. The empirical results shown in Tables 3 and 4 demonstrate that a higher extent of guests' analytical thinking contributes to a stronger association between negative sentiment and rating scores. However, the moderation effect on the relationship between positive sentiment and rating scores is not significant. This is because negative reviews provide more diagnostic information that is logical and relevant to reviewers' judgment (Smith et al., 1998). Individuals high in analytical thinking rely on logical connections (Epstein et al., 1996) and thus focus on diagnostic information in negative reviews. These people are more able to link their rating behaviors to consumption sentiment than individuals low in analytical thinking and tend to give lower ratings for negative sentiment. This results in a high moderation effect on the association between negative sentiment and rating scores. Nonetheless, researchers have found that people may imitate each other in evaluating products (Banerjee, 1992; Chen, 2008), and prior positive ratings create accumulating positive herding and significant positive bias in individual rating behavior (Lev et al., 2013). People with low analytical thinking tend to give high ratings to Airbnb listings because of the positive skew of existing ratings and positive social influence. People with high analytical thinking logically connect their rating behaviors to consumption sentiment, and as a result, rate the listings high as well if their consumption sentiment is positive. Whether with high or low analytical thinking, guests have the intention to give high ratings to the listings for positive sentiments. Therefore, the moderation effect on the association between negative sentiment and rating scores becomes insignificant.

A similar biased pattern can be seen for the moderation effect of guests' authenticity. Both the "face-threatening act" and the reciprocal review system have minimal impacts on Airbnb guests' willingness to present high rating scores consistent with their positive sentiment regardless of whether they have high or low authenticity. Guests with high authenticity are willing to give high rating scores for their positive consumption sentiment toward Airbnb listings because they are honest. People with low authenticity are also willing to rate the listings high for their positive consumption sentiment because providing high ratings does not cause a face-threatening problem or vindictive acts from the hosts in the reciprocal review system. Whether with high or low authenticity, guests are willing to give high ratings to the listings for positive sentiments. The moderation effect of ***Authenticity*** on the association between positive sentiment and rating scores is consequently not significant. However, high authenticity encourages guests to overcome the two obstacles and voice negative sentiment in their rating scores. Thus, guests with high authenticity are more willing to provide low ratings than guests with low authenticity. The moderation effect of ***Authenticity*** on the link between negative sentiment and rating scores becomes obvious.

The estimated coefficients of the control variables also represent various findings that can help Airbnb hosts understand how to raise their review rating scores by improving their services. It is no surprise that service quality plays an important role in satisfying guests and driving them to increase their ratings. Hosts who have fewer rooms can be more focused and provide better services, which in turn help them earn higher rating scores (Xie and Mao, 2017). A high response rate, which signals efficient services provided by hosts, is another driver of rating scores. In terms of renting policies, a more flexible cancellation policy better satisfies guests and leads to higher rating scores. Interestingly, although the instant booking policy is convenient for guests, this policy has a negative impact on ratings. This finding reflects the fact that the instant booking policy can potentially diminish the initial communication between guests and hosts to build trust, which is likely to cause an unmatched host-guest encounter (Cheng and Foley, 2018).

6.2. Theoretical and managerial implications

This paper contributes to the tourism literature by adding knowledge about peer-to-peer accommodation management. As one of the pioneers of the sharing economy, P2P accommodation businesses have attracted increasing research attention, but the related discussions are still limited due to the short history of these businesses. Our paper supplements the existing research and elucidates the relationship between guests' sentiment and review ratings of accommodations. This relationship has been disclosed in traditional hotel businesses (Geetha et al., 2017), and our findings provide further evidence under the P2P rental context. More importantly, we have tracked the root of this relationship by looking into customer satisfaction and affect studies. Guest satisfaction results from the evaluation of performance based on expectations and reflects the emotional reaction to consumption. We argue that the evaluation and emotions toward hosts' services are reflected by guests' sentiment, which is thus linked to guest satisfaction and determines review ratings. This argument sets the theoretical foundation for the connection between guests' sentiment and review ratings but has been overlooked in the tourism and hospitality literature.

Investigating the moderation effects of analytical thinking and authenticity also constitutes a theoretical contribution of this paper. Previous studies have proven the link between customers' sentiment and review ratings for different products (Lak and Turetken, 2014; Qiu et al., 2018; Rani et al., 2017) but failed to examine when the link is stronger. Data sets with a disparate mix of reviewer characteristics could lead to diverse conclusions, and our study suggests that the strength of the association between sentiment and ratings varies across guests with different extents of analytical thinking and authenticity. The moderation effects of guests' analytical thinking and authenticity extend our knowledge about the connection between sentiment and rating scores.

The managerial implications of this paper are twofold. First, the valence of online reviews has been shown to reduce purchase uncertainty (Zhu and Zhang, 2010) and drive online sales (Liang et al., 2017). Our findings expose the fact that there may be more to guests' ratings than just hosts maintaining high service quality. The sentiment generated from service encounters may be more important for customer satisfaction than perceived performance (Krampf et al., 2003). As suggested by Oliver et al. (1997), meeting guests' expectations is inadequate for marketing. Hosts and Airbnb marketers must find ways to elicit guests' delight in service encounters to obtain high satisfaction and rating scores.

Second, our study can help Airbnb hosts and marketers look beyond numerical rating scores into the textual content of guest reviews. Reviews are often multifaceted and incorporate rich information that cannot be entirely captured by a single scalar value (Archak et al., 2011). Practitioners should therefore seek to understand what guests provide in reviews. Sentiment analysis has been illustrated as a useful tool for this purpose in our study. Review content contains information about guests' evaluation of the services and promotions offered by hosts or the Airbnb platform. Sentiment analysis helps uncover this information from textual reviews, providing hosts or Airbnb marketers accurate insight into whether their marketing efforts please guests.

7. Limitations and future research

This paper applies sentiment analysis to parse the review content of Airbnb listings to examine the association between guests' sentiment and rating scores. To better decipher guest satisfaction proxied by ratings, the moderation effects of analytical thinking and authenticity are considered. While sentiment analysis provides insights into the positive and negative dimensions of review comments, further research is encouraged to apply a more precise embedded dictionary to summarize various other dimensions of emotions since emotions can be diversified (Wang et al., 2016; Westbrook and Oliver, 1991). This will contribute to further discussion on online reviews and guest satisfaction. Additionally, our study is confined to reviews in English. Future research can be undertaken in a bilingual or multilingual context for cross-cultural analysis. This would enrich our cross-cultural understanding of the link between review sentiment and guest satisfaction. Furthermore, factors related to the properties of the listings and platform, the guests' experiences in the destinations, as well as the guests' and hosts' personality and cultural background can be important determinants of guests' ratings. Future research can use field experiments to collect data related to these confounders for more precise empirical analyses. The links among these variables, the control variables used in our empirical analysis and sentiments could also be a promising topic for future investigations.

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