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Listening to online reviews: A mixed-methods investigation of customer experience in the sharing economy

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ABSTRACT

Understanding customer experience is an essential part of service operations for sustaining business in the sharing economy. We investigate the relationship among customer experience, perceived value, and customer loyalty from a stimulus-organism-response (S-O-R) perspective. Using a dataset of 4166 listings in a leading Chinese accommodation-sharing platform and text mining and econometric methods to analyze online customer reviews, we find that customer experience manifests in the physical environment and human interaction dimensions. The results show a positive association among customer experience, perceived value, and customer loyalty. Notably, the physical environment and human interaction are equally important in influencing customers' value judgments about their consumption experience. Moreover, perceived value has a stronger positive effect on attitudinal loyalty than on behavioral loyalty. This study adds new insights into the customer experience-perceived value-customer loyalty path by showing that the physical environment and human interaction have the same importance in affecting perceived value and identifying the subtle difference between attitudinal and behavioral loyalty influenced by perceived value in the accommodation-sharing economy. Furthermore, these findings provide managerial insights for service operations management and marketing strategy planning.

1. Introduction

The past five years have witnessed the rapid growth of the sharing economy, which has encouraged the utilization of idle resources through the temporary transfer of usage rights [1]. Sparked by the growth of Airbnb and Uber, sales revenue arising from the sharing economy is projected to increase to 335 billion dollars by 2025, and companies operating in the sharing economy are expected to grow by 2133% in 12 years.[1] In the United States, 83% of people are familiar with sharing services, and 56.5 million people have used sharing services.[2] In China, the transaction scale of the sharing economy in 2019 reached 3282.8 billion yuan, and the number of participants was approximately 800 million.[3] The sharing economy has been considered a “creative disruption” because its innovative business model connects strangers through collaborative consumption and value cocreation with the help of IT platforms [2]. In particular, the increasing connectivity via IT platforms stimulates customer demand, and service providers are pursuing new growth opportunities to attract and retain customers.

Peer-to-peer (P2P) accommodations, a business model of the sharing economy widely used in the accommodation sector, have gained popularity because customers can obtain a sense of community belongingness and experiences authentic to local customs in offline hospitality services through online bookings [3,4]. P2P accommodation involves a person renting his/her houses or rooms to another person in exchange for money, which is enabled by online platforms [5]. Unlike traditional hotels, two attractive features of P2P accommodations lie in social interaction and the low cost of quality accommodation [4]. Indeed, the emergence of P2P accommodations has transformed

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[1] https://spendmenot.com/blog/sharing-economy-statistics/ (accessed on 14 August 2020)
[2] https://www.statista.com/topics/4694/sharing-services-in-the-us/ (accessed on 14 August 2020)
[3] http://www.sic.gov.cn/News/568/10429.htm (accessed on 14 August 2020)

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hospitality services and poses significant challenges to the hotel industry [2]. It is worth conducting an in-depth investigation into customer experience and behavior in the P2P accommodation sector.

Previous studies have focused on customers' participation motivation, customer experience, and use/purchase intention in P2P accommodations [6,7]. Evidence has shown that hedonic (adventure, gratification, sharing, and friend-seeking) and utilitarian motivations (e.g., cost savings, resource efficiency, and information acquisition) drive customers to participate in accommodation-sharing services [6]. Studies investigating customer experience have reported that customers value diverse service or product attributes at various accommodation-sharing levels [3,8]. Prior literature has demonstrated that customer trust, formed by host attributes, listing characteristics, and contextual elements, is a crucial factor affecting customer purchases [6,7]. Nevertheless, there is limited literature that gauges the antecedents of customer loyalty from the attitudinal and behavioral dimensions in choosing P2P accommodations. The mediation process through which customer experience affects customer loyalty is also underinvestigated. Due to the exchange of money in P2P accommodations, customers usually compare the encounter experience with their expectations and judge the value from what they “gave” and “gained” in this transaction [4]. Perceived value (e.g., value for money) is critical organism feedback because it mirrors the overall assessment of the customer encounter experience [9]. In addition, evidence has shown that “value” is a salient topic in P2P accommodations [9], which is driven by customer experience and at the same time shapes customer loyalty [10]. Accordingly, we aim to examine the mediating role of perceived value between customer experience and customer loyalty in the sharing economy context.

Customer experience, depicting how customers respond to staged encounters under a specific condition, derives from a set of interactions between a customer and the living environment, service providers, and other guests [11]. Experience clues shape customer experience, including functional and mechanic clues that are emitted by things and human clues that are emitted by people [12]. Customer experience involves the physical environment, defined as the tangible components of the physical experience (functional and mechanic clues), and human interaction, defined as intangible elements sensed from people (humanic clues) [13]. Previous research has posited that the physical environment and human interaction are the two manifestations that shape the customer experience in accommodation services [13,14]. A positive association between customer experience involving the physical environment and human interaction dimensions and perceived value has been found [13–15]. Nevertheless, the literature comparing the influence of these two dimensions on customer value has yielded mixed results [10,13]. Some scholars have found that the physical environment appears to be stronger than human interaction in affecting emotive and cognitive value [13]. However, other researchers have refuted this idea, arguing instead that customers value host hospitality and social interaction more than the physical environment in the accommodation-sharing economy [3,4]. These contradictory results call for further investigation on which dimension of customer experience exerts a more decisive influence on perceived value in P2P accommodations.

Achieving customer loyalty is an effective way for marketers to generate profit by retaining regular customers [16]. There are two types of customer loyalty: attitudinal loyalty and behavioral loyalty [17]. Attitudinal loyalty represents the commitment to the product, and behavioral loyalty refers to customers' repeated repurchases of a product [16]. Investigating the relationship between perceived value and customer loyalty has gained momentum, especially in experiential industries [14,15]. Most studies have focused on the perceived value-attitudinal loyalty link, and less attention has been given to the relationship between perceived value and behavioral loyalty [14]. In contrast to attitudinal loyalty, behavioral loyalty requires greater customer commitment and increased benefits [18]. In this study, we aim to investigate and compare the effects of perceived value on both attitudinal loyalty and behavioral loyalty.

Our research question is “what and how are the relationships among customer experience (i.e., physical environment and human interaction), perceived value, and customer loyalty (i.e., attitudinal loyalty and behavioral loyalty) in P2P accommodations?” This study is rooted in stimulus-organism-response (S-O-R) theory. The S-O-R framework emphasizes the role of an organism, which is triggered by environmental stimuli and stimulates a response [19]. The physical environment and human interaction dimensions are experience clues that can act as environmental stimuli during customer encounter experiences [13]. Perceived value is based on internal feedback because customers often make a value judgment that derives from their consumption experience. Customer loyalty, both attitudinal and behavioral loyalty, is the response formed by a customer's value evaluation of the experience. In addition, we also extend the S-O-R framework to compare the effects of different stimuli in affecting organism feedback and investigate whether organism feedback differs in influencing various responses.

To address our research questions, we integrate text mining with econometric analysis to systematically and deeply examine the relationship among customer experience, perceived value, and customer loyalty using 4166 listings and 40,459 customer reviews in Xiaozhu.com. Prior studies have investigated customer experience in P2P accommodations using text mining to extract customer opinions from the English context, including automatic cluster analysis and manual deduced analysis [3,8]. We provide a wealth of knowledge on dealing with unstructured data in the Chinese language using a mixed-methods approach of integrating latent Dirichlet allocation (LDA), machine learning algorithms, and dictionary-based sentiment analysis to summarize topic-specific sentiment. In terms of text mining, we not only efficiently process a large amount of text and make the machine accurately understand natural language but also conduct topic, entity, and relation extraction to obtain useful information [20]. First, to determine what dimensions the customer experience includes, we employ LDA to conduct topic modeling and identify the general topics. Second, we use machine learning algorithms to predict the topics at the sentence, review, and product levels. Third, we take advantage of dictionaries to perform sentiment analysis to extract topic-specific sentiment. To the best of our knowledge, this study is the first investigation that attempts to obtain topic-specific sentiments from unstructured text and link them to actual customer behavior toward P2P accommodation services using econometric analysis. We find that the perceived dimensions of the physical environment and human interaction shape customer experience, positively affecting perceived value. Interestingly, the physical environment is as crucial as human interaction for customer value judgment in P2P accommodations. We also find that perceived value is positively associated with attitudinal loyalty and behavioral loyalty. Notably, the positive effect of perceived value on attitudinal loyalty is more prominent than that on behavioral loyalty. Moreover, we provide strong evidence that the relationship between customer experience (i.e., physical environment and human interaction) and customer loyalty (i.e., attitudinal loyalty and behavioral loyalty) is mediated by perceived value.

2. Theoretical foundation and hypotheses

2.1. The S-O-R framework

The S-O-R framework indicates that the link between environmental stimuli and behavioral responses is mediated by internal emotional feedback, such as pleasure and arousal [19]. The framework is applied in social commerce to explain the psychological processes of customers who encounter environmental stimuli in making purchase decisions [21]. In experiential marketing, the S-O-R model highlights the vital importance of experience clues related to product or service providers, determining customers' inner feelings and behavioral intentions [22]. Based on the S-O-R framework, previous research has demonstrated that product and contextual features are the factors that stimulate customers' perceived value, thereby affecting their repurchase intentions [21]. Moreover, the perceived value resulting from the virtual shopping experience (stimulus), such as esthetic appeal and functionality, can promote customer loyalty in behavioral and attitudinal dimensions [15]. Atmospheric clues, such as tasks and social clues, play a vital role in stimulating consumers' mentality and subsequent behavioral intentions [23]. Overall, the S-O-R model has an advantage in capturing the mediation process between customer experience and behavioral intentions.

In the accommodation-sharing service industry, customers can encounter products, services, and service personnel offline after online booking. The environment linked to humans or things in the actual experience can become a stimulus that may influence customers' attitudes and behavioral intentions [3]. Previous research has found that environmental clues positively affect customers' responses [13]. Moreover, evidence has shown that customers' responses depend on environmental clues, including cognitive (e.g., physical functionality) and emotive (e.g., interaction with humans) clues. Specifically, scholars have found that amenities, location, and host communication affect customer satisfaction in P2P accommodations [8]. However, these studies neglect the mediators between customer experience and behavioral intentions. In P2P accommodations, there exists a series of organism feedback, such as perceived value, that mirrors customers' progressive psychological changes caused by customer experience (stimulus). Considering that the S-O-R model interprets the importance of organism feedback triggered by the context (stimulus) in affecting customers' subsequent responses, we employ this model as the theoretical framework to investigate the relationship among customer experience, perceived value, and customer loyalty.

Using the S-O-R framework, we aim to link the accommodation experience stimulus (S) with the subsequent psychological and behavioral outcomes (O, R). Fig. 1 presents the research framework that summarizes the proposed hypotheses as follows. Based on the S-O-R model, human interaction and the physical environment, as two dimensions of customer experience, are treated as stimuli. Therefore, we assume that perceived value is the outcome of environmental stimuli (Organism), which influences customer loyalty in the attitudinal and behavioral dimensions (Response).

2.2. Customer experience as stimulus

Customer experience is an essential concept in studying and interpreting customer behavior [12]. Holbrook and Hirschman proposed an experiential view of consumption, defining customer experience as a subjective state of consciousness related to the symbolic, hedonic, and esthetic nature of consumption [24]. Later, studies of experiential marketing considered customer experience as an integration of sensory, affective, cognitive, physical, and social experiences [25]. In the hospitality sector, customer experience is defined as the takeaway impression when customers encounter products, services, and businesses [12]. Evidence from an exploratory study on hotels suggests that the physical environment and human interaction constitute the perceived dimensions of the hotel guest experience [11]. Four key elements construct the physical environment dimensions: ambiance, multisensory, space and function, and signs/symbols/artifacts. In terms of the human interaction dimensions, attitude, professional behavior, proactive service, and socialization are essential factors [11]. Overall, interactions with physical or human elements are crucial to shaping customer experience [13].

As experience-intensive services, P2P accommodations have aroused scholars' interest in examining customer experience in hospitality destinations [8,9]. Customer experience is characterized as a product attribute generated by customers' interactions with the physical environment and people [11]. Previous studies have consistently agreed that the physical environment (PE) and human interaction (HI) are two prominent elements underpinning the customer experience during their stay, as these clues reveal some information concerning product- and service-related attributes [13,26]. Notably, online customer reviews have become a trustworthy information source for researchers to capture hospitality experiences in the accommodation sector [8]. Table 1 presents the dimensions of customer experience in P2P accommodations. Amenities, cleanliness, and location are aspects of PE that customers care about [8,27], while communication and the host-guest contact are aspects of HI that influence customer behavior [3,8,9]. In the accommodation experience, interactions with things (PE) and people

Table 1
Customer experience in P2P accommodations.

Sources	Attributes	Research samples
[3]	PE: room, amenities, external environment HI: communication, host interaction, neighbor interaction	Reviews from 802 listings in Airbnb and Expedia, respectively in Los Angeles
[8]	PE: amenities, cleanliness, homeliness, location, transport HI: host (communication, helpfulness, flexibility for check-in/out)	169,666 Airbnb reviews in London
[28]	PE: cleanliness, safety and security, location, amenities, decoration HI: communication, atmosphere, flexibility, services	2938 Airbnb review data in Sydney
[9]	PE: physical utility, sensorial experience, core service, and sense of security HI: guest-host relationship, social interaction, and local touch	Thirty-four in-depth interviews for Airbnb users in China
[27]	PE: location, neighborhood, property (facilities and atmosphere) HI: host (service and hospitality)	41,560 Airbnb reviews in Portland

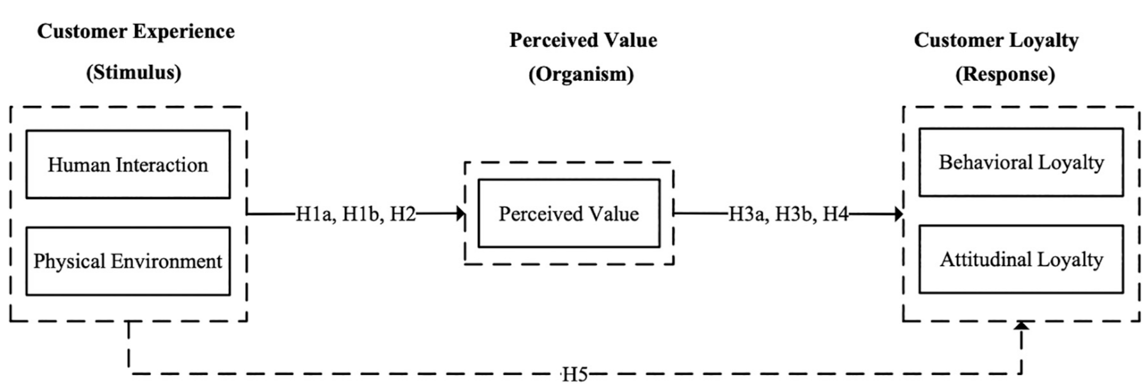

Fig. 1. Research framework.

(HI) are critical to shaping customer experience [11].

2.3. Perceived value as organism

Perceived value is an abstract concept, depicting the "overall assessment of the utility of an offering according to perceived benefits and costs" [29]. It incorporates the economic, functional, emotional, and symbolic dimensions of customer value [30]. In a parallel vein, four distinct dimensions of experiential value have been proposed: cognitive, hedonic, social, and ethical [31]. Previous research has shown that a customer's judgment of perceived value depends upon the customer experience because "perceived" reflects the experiential view [13]. In purchasing a tourism product, perceived value is a subjective construct that varies at different times because it manifests before, during, and after the experience [32]. In this study, we consider the postpurchase perceived value of a product or service as the organism feedback to customer experience.

Scholars have found that experience clues are an essential premise for perceived value in P2P accommodations [14]. Specifically, evidence has shown that substantive staging and communicative staging of the hotel servicescape have a significant influence on value perception. In addition, it has been found that the PE and HI positively affect emotive value and cognitive value in a hospitality setting [13]. On the one hand, scholars have supported that the PE is positively associated with perceived value and customer behavior [32]. Prior literature has found evidence supporting the importance of tangible clues and argued that physical surroundings could contribute to sales performance [13,14]. The quality of accommodation and ambient surroundings are functional features that have strong correlations with customer value [33]. On the other hand, HI has also been considered a critical element that affects customer attitudes [8]. Numerous studies have consistently demonstrated that travelers emphasize host hospitality and social contact in tourism destinations [27,34]. Social interaction is also viewed as a desirable element for customers to have unique experiences, which affect customer value [32]. Thus, we propose that.

Hypothesis 1a. The customer experience of the physical environment is positively associated with perceived value.

Hypothesis 1b. The customer experience of human interaction is positively associated with perceived value.

Numerous studies have reached a consensus that an attractive element of P2P accommodations originates from social interaction and hospitableness from humans [4]. Compared with traditional hotels that prioritize tangible characteristics and the PE, P2P accommodations highlight the vital importance of social interaction and a hospitable atmosphere [27,34]. This home-sharing service offers face-to-face communication for guests to share anything with others, which can help customers satisfy their hedonic motivations of participating in P2P accommodations, such as "making new friends" and "creating a long-term relationship" [6]. Evidence has shown that effective communication can form a trustworthy image of providers, which positively impacts customer attitudes [35]. Using text-mining approaches to online customer reviews, previous research has found that building a relationship and forming an emotional bond in offline interactions are salient features [4]. Unlike the PE that focuses on functionality, HI is a major attraction that enhances customer emotional attachment and stickiness to a product or service provider [35]. Through experiments and surveys, scholars have found that social clues positively affect perceptions of human connections, which promote the formation of perceived value [13]. In P2P accommodations, customers can come into contact with things (e.g., products) or people (e.g., service providers). It has been found that the social dimension of HI can generate customer trust and lead to purchase intentions [33]. Evidence has shown that social interaction and host hospitality during customer encounter experiences enhance perceived enjoyment and pleasure [27,34]. Given that HI is the added service provided by the accommodation-sharing economy, we argue that HI has a more decisive influence on perceived value than the PE does.

Hypothesis 2. The positive effect of human interaction experienced by customers on perceived value is stronger than that of the physical environment.

2.4. Customer loyalty as response

Customer loyalty is a favorable outcome of successful customer experience management [16], expressed by a strong repeat purchase intention and commitment to a particular company or service provider [36]. There are two manifestations of customer loyalty: attitudinal and behavioral [17]. With computer-mediated platforms, customers can express their intentions to recommend and repurchase by posting online reviews. In this context, recommendations and repurchase intentions represent customer loyalty in attitude [37]. Similarly, behavioral loyalty describes the repeated repurchase of the product [16]. In this study, we consider attitudinal loyalty and behavioral loyalty as two dimensions of customer loyalty as responses to internal feedback and environmental stimuli.

Previous studies have demonstrated that postpurchase perceived value has a positive effect on customer loyalty [14,38]. Evidence has supported that perceived value determines revisiting intention and word-of-mouth (WOM) intention in hotel businesses because customers are likely to choose the same product from which they have obtained positive experiential value from the purchased product [14]. In the shopping environment, customer loyalty (e.g., repurchase intentions) is the outcome of delivering superior value [39]. Similarly, in P2P accommodations where customers encounter the PE and people with different backgrounds, perceived value is a critical strategic product attribute that illustrates customer repurchase and brand loyalty because customers assess the perceived benefits to perceived costs [10]. Thus, we hypothesize that.

Hypothesis 3a. Customer perception of perceived value is positively associated with attitudinal loyalty.

Hypothesis 3b. Customer perception of perceived value is positively associated with behavioral loyalty.

Following previous research, true loyalty is the integration of a favorable disposition toward (attitudinal loyalty) and a repeat purchase of the brand (behavioral loyalty) [36]. Evidence has demonstrated that behavioral loyalty is influenced by attitudinal loyalty [36]. Prior literature has focused on examining the relationship between perceived value and attitudinal loyalty, indicating their positive link when using a product [40]. Specifically, perceived value is the driver of revisiting intention and WOM intention [40]. However, the formation of behavioral loyalty requires more conditions than attitudinal loyalty, such as greater customer commitment and increased benefits [18]. Evidence has provided support for the perceived value-attitudinal loyalty-behavioral loyalty path in the service market [39]. Considering that the perceived dimensions of customer value and attitudinal loyalty depict psychometric properties rather than behavioral patterns, we assume that the positive link between perceived value and attitudinal loyalty is stronger than that between perceived value and behavioral loyalty in P2P accommodations.

Hypothesis 4. The positive effect of customer perceived value is stronger on attitudinal loyalty than on behavioral loyalty.

Prior studies have confirmed that perceived value, as a value judgment of the encountered service or product, is a crucial mediator between customer experience and customer loyalty [10,14]. For example, substantive and communicative servicescapes play an essential role in eliciting the perceived value of the guest experience, which helps generate higher positive WOM for the company [10]. Moreover, scholars have found that experience clues in the accommodations industry can bring emotive value and affect brand loyalty [14]. In the experiential environment, the quality of products is an important element in forming perceived value, which influences customer satisfaction and loyalty [38]. Research has shown that perceived value, as an essential antecedent of behavioral intentions, including satisfaction, WOM, and repurchase intentions, is the outcome of customer experience [30]. Based on the S-O-R approach, previous research has found that perceived ubiquity, contextual offerings, visual attractiveness, and app incentives are dimensions of customer experience that stimulate the perceived value of shopping and shape repurchase intentions [21]. Similarly, in P2P accommodations, customers can have offline interactions with the home-sharing environment and service providers. In this context, customer perception of tourism destinations involves the PE and HI, which has a significant influence on perceived value, thereby affecting behavioral intentions [10]. Accordingly, we hypothesize that.

Hypothesis 5. The positive effects of customer experience of the physical environment and human interaction on customer loyalty, including attitudinal loyalty and behavioral loyalty, are mediated by perceived value.

3. Data and methodology

3.1. Dataset and samples

To identify what attributes of P2P accommodations customers value, we collected data from Xiaozhu.com, a leading Chinese online short-term rental. First, Xiaozhu.com, established in 2012, has recently experienced remarkable growth as an online accommodation-sharing platform in China. It now offers over 800,000 listings in more than 700 cities with approximately 50 million active users.[4] Second, given the explosive popularity of the sharing economy, Xiaozhu.com is preferred as the representative P2P accommodation operator in the country [7,41]. Finally, considering the availability of information, we can access a large number of customer reviews because Xiaozhu.com provides more opportunities for host-guest interaction and encourages customer feedback.

Data were collected in March 2017 using Python from Beijing, where customers account for the vast majority of the Chinese short-term rental market relative to other cities. The sample comprises 4166 listings and 40,459 customer reviews from 2012 to 2017. The comments that had no text information were removed, and 39,525 customer reviews remained. In addition to customer reviews, we obtained some information about listing characteristics (e.g., price) and host attributes (e.g., gender).

3.2. Research methodology

To extract the variables of interest, we capture relevant topics and their sentiments from customer reviews to determine metrics for customer experience (i.e., PE and HI), perceived value, and attitudinal loyalty. Following the previous literature on text analysis [20], we adopt LDA to identify the general topics discussed in customer reviews from a holistic perspective, which is called topic extraction. Next, from an individual perspective, we identify the topic-specific sentiment for each sentence constituting customer reviews. Specifically, we employ machine learning algorithms to predict the topics and calculate their sentiment scores based on dictionaries. We then divide this step into two aspects: topic prediction and sentiment extraction. Overall, we use a mixed-methods approach integrating topic extraction, topic prediction, and sentiment extraction to measure the salient attributes of P2P accommodations, illustrated in Fig. A.

3.2.1. Step 1: topic extraction using the LDA model

Topic modeling is a text-analysis approach that identifies the general topics presented in unstructured text [20]. LDA, a standard tool of topic modeling, is an unsupervised machine learning algorithm that identifies hidden topics from large-scale documents [42]. The topic-generation model consists of three layers of words, topics, and documents. To make the machine recognize natural language, we conduct a series of data preprocessing for subsequent topic modeling, including data acquisition, tokenization, cleaning, spelling, keeping user-defined words, and removing stopwords,[5] as illustrated in Table A. After that, we train the model to determine the number of topics implied in the unstructured text during topic modeling. Based on extant studies [42,43], perplexity is a metric of evaluating the quality of the training model that can help identify the appropriate number of topics and recognize what topics are contained in certain documents with uncertainty. According to perplexity calculations, we find that the optimal number of topics is 50, supporting a well-accepted training model. Furthermore, we run the LDA model with the optimal parameters derived from perplexity calculations using Python and obtain thirteen

Table 2
Topics extracted from online customer reviews.

Dimensions	Topics	Codes	Feature words
Attitudinal loyalty	repurchase intentions	8, 16, 21, 36	come back, next time, repurchase, continue to live
	the willingness to recommend	6	recommend, highly recommended, next time,
Perceived value	enjoyment and pleasure	1, 34, 44	experience, pleasant, satisfaction, nice, perfect, happy, valuable
	value for money	50	price, value for money, affordable, cheap, cost-effective, value, reasonable
PE	aesthetics and comfort	13, 24, 33, 41	neat, tidy, comfortable, room, warm, spacious, lighting, French windows
	amenities	11, 25, 31, 42, 48	kitchen, complete, TV, refrigerator, washing machine, microwave oven, kitchenware, air conditioner, hot water, internet, induction cooker, water heater
	surroundings	36, 49	ambient, disturb, quiet, greenbelt, surroundings
	location and transportation	3, 9, 12, 14, 20, 26, 32, 47	convenience, nearby, shopping, location, bus, supermarket, convenient, transportation, subway
	safety facilities	45	safety, secret lock, access control, security guard, access card, key, elevator
HI	reliability	10	picture, photo, description, match, consistent, actual, real, difference, same
	hospitality and caring	5, 7, 15, 17, 22, 23, 27, 39, 40, 43	gentle, nice, warm, happy, caring, intimate, enthusiastic, kind, affect
	professionalism	19, 35, 37, 46	check out, telephone, clean up, deposit, key, in advance, help, solution, patient, communication, answer, feedback, contact, satisfy, positive
	social interaction	2, 4, 18, 28, 29, 30	friend, parents, children, family, mother, baby, host, dinner, tourism

[4] https://www.xiaozhu.com/ (accessed on 14 August 2020)

[5] https://github.com/goto456/stopwords (accessed on 14 August 2020)

topics, summarized in Table 2. The thirteen topics are "repurchase intentions", "the willingness to recommend", "enjoyment and pleasure", "value for money", "aesthetics and comfort", "amenities", "surroundings", "location and transportation", "safety facilities", "reliability", "hospitality and caring", "professionalism", and "social interaction". Following the previous literature [6,11,37], we divide these thirteen topics into four primary dimensions: attitudinal loyalty, perceived value, PE, and HI.

3.2.2. Step 2: topic prediction using the SVM algorithm

After identifying the general topics included in the customer reviews, we adopt four steps to predict the topics for each review using machine learning algorithms, as illustrated in Fig. B. The first step concerns text preprocessing. We use punctuation as a separator to segment 39,525 paragraphs/customer reviews into 355,231 sentences because a sentence is the smallest complete semantic unit of extracting opinions [44]. The second step is to transform natural language into a machine-recognizable form for each sentence. Based on word frequency and term frequency-inverse document frequency (TF-IDF), we choose feature words and construct a vector space model weighted by word frequency to represent each sentence. In the third step, we manually label 9438 sentences in 1200 customer reviews as random samples, as shown in Table B. We then divide them into two sets: a training set and a testing set. The former is used to train the model, while the latter is used to evaluate the accuracy of the generated trained model [45]. In addition, we call different classifiers to learn the training set and predict the topics in the testing set. According to the precision rate, recall rate, and F1 score, as well as the micro average and macro average metrics [46], we find that the support vector machine (SVM) algorithm performs better than other classifiers in topic prediction (micro average: 76%, macro average: 76%), as shown in Fig. C. The classification performance is well accepted because this is a multicategory prediction. The final step is topic prediction, in which we employ the SVM algorithm to predict the sentence-level topic by learning the annotated samples. Fig. 2 presents the percentage of each topic in the prediction result. Overall, the topics, namely, "aesthetics and comfort", "hospitality and caring", "location and transportation", and "enjoyment and pleasure", are salient in P2P accommodations.

3.2.3. Step 3: sentiment extraction based on dictionaries

Sentiment analysis is a process of extracting users' opinions from subjective text, including positive, negative, and neutral opinions [46]. We apply dictionaries (i.e., a predefined list of words) to calculate the sentence-level, review-level, and product-level sentiment because dictionary approaches can help measure constructs [20]. To build dictionaries in support of sentiment analysis, we collect dictionaries from "vocabulary collection for sentiment analysis" released by HowNet[6] and user-defined dictionaries extracted from our research samples [47]. There are two main steps in extracting product-based sentiment: The first step is to calculate the sentiment score of each topic that a review conveys, and the second step is to gain the sentiment score of each topic that a listing receives, as illustrated in Fig. D. Considering that a sentence consists of degree words (e.g., very and quite), reverse words (e.g., not and no), and emotional words (e.g., good and bad), we identify the emotional words and judge the position of the degree words and reversal words [48]. According to the types of degree words, we divide the semantic weight into four levels: 0.5, 1, 1.5, and 2 points [49]. Based on the combination rules of three kinds of words and calculation formulas of dictionary-based sentiment in the Chinese language [50], we calculate the sentiment score for each sentence. Following the way of assigning the sentiment to each identified topic for each product used in previous research [51], we average the sentiment score of sentence-level topics for each review and then average the sentiment score of the review-level topic for each listing. Considering that consumers may be cognitively unprepared, or unaware of the need, to express any sentiment for each topic, we refer to prior research [52] and code all the missing values regarding the sentiments of thirteen topics as "0". According to the previous literature [53], we normalize the topic-specific sentiments to range from 0 to 1, as shown in Table 3. These topic-specific sentiments are used to measure the thirteen extracted topics.

3.3. Model specification

After extracting the topic-specific sentiment, we aim to measure the customer experience (i.e., PE and HI), perceived value, and attitudinal loyalty dimensions. Previous studies have argued that the sentiment of a high-level aspect is determined by the average sentiment score of its constituent elementary aspects [45]. Similar to the numeric rating in which the overall rating is the average aspect rating, the average sentiment score of subdimensions can reflect the general satisfaction level of a certain dimension generated by customers [52]. Accordingly, because repurchase and recommendation intentions can reflect customer loyalty in attitude [37], we calculate an average sentiment score of "repurchase intentions" and "the willingness to recommend" to measure attitudinal loyalty. Considering that the PE and HI shape customer experience [13], we calculate an average sentiment score of "aesthetics and comfort", "amenities", "surroundings", "location and transportation", and "safety facilities" to measure the PE, while an average sentiment score of "reliability", "hospitality and caring", "professionalism", and "social interaction" is used to measure HI. Moreover, due to that perceived value consists of hedonic value and utilitarian value [6], we adopt an average sentiment score of "value for money" and "enjoyment and pleasure" to measure perceived value.

In addition to unstructured customer-generated content, we include structured data to examine the effects of customer experience on perceived value and customer loyalty. To better illustrate customer loyalty, we capture the number of guests who posted reviews via online platforms and who repeatedly purchased the same property to measure behavioral loyalty [35]. In terms of control variables, prior research has shown that host attributes are key for building trust in P2P accommodations [7]. We add some variables regarding service providers, including gender, response rate, confirmation time, acceptance rate, sales volume, and homepage, controlled in the model. In addition, the listing characteristics displayed on online platforms also play an essential role in affecting customer choices [41]. In particular, as a signal of product quality and cost, price significantly affects customer purchases [4]. We include price as the control variable. In addition, location is pivotal for guests in choosing P2P accommodations [27]; we consider the district of Beijing as the control variable.

Table 4 describes the variables of interest, and Table 5 presents the correlations among variables. There are correlations with "high significance" among variables. The absolute value of the correlation coefficients ranges from 0.003 to 0.545. In addition, we conduct the variance inflation factor (VIF) test in subsequent regression analyses. All the results show no serious multicollinearity issue because the VIF is far less than 10.

To address the research questions, we employ the following econometric models to examine the effects of customer experience involving the PE and HI on perceived value and customer loyalty (i.e., attitudinal loyalty and behavioral loyalty). All the variables are standardized. We adopt ordinary least square (OLS) regressions to estimate perceived value and customer loyalty for each listing i as follows.

$$\begin{aligned} Perceived\ value_i &= \alpha_0 + \alpha_1 Physical\ environment_i + \alpha_2 Human\ interaction_i \\ &+ \alpha_3 Price_i + \alpha_4 District_i + \alpha_5 Gender_i + \alpha_6 Response\ rate_i \\ &+ \alpha_7 Confirmation\ time_i + \alpha_8 Acceptance\ rate_i + \alpha_9 Sales\ volume_i \\ &+ \alpha_{10} Homepage_i + \varepsilon_i \end{aligned} \quad (1)$$

[6] http://www.keenage.com/download/sentiment.rar. (accessed on 14 August 2020)

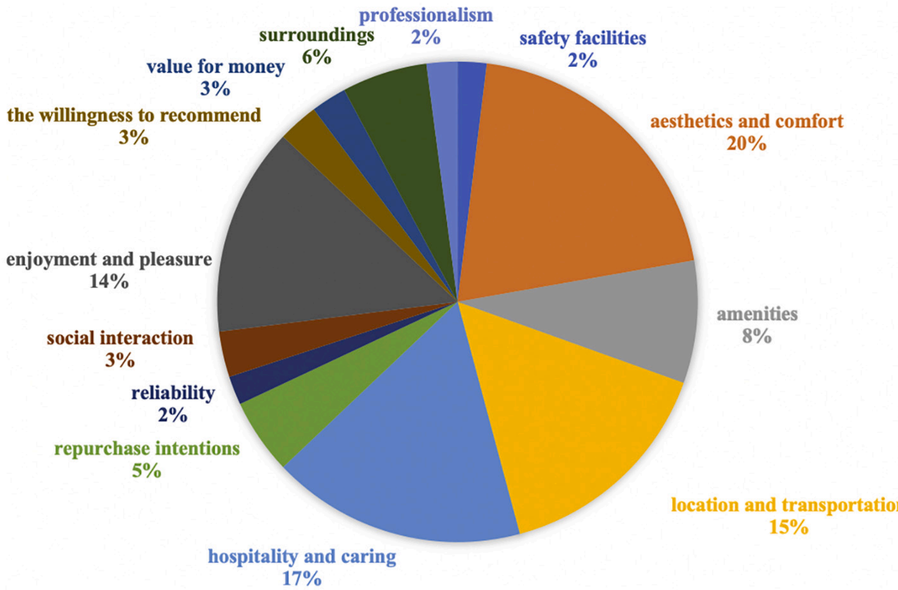

Fig. 2. Percentage of each topic.

Table 3
Description of topic-specific sentiments.

Dimensions	Topics	Description	Mean	S. D	Min	Max
Attitudinal loyalty	repurchase intentions	The normalized sentiment score of the topic "repurchase intentions" for a listing	0.735	0.115	0	1
	the willingness to recommend	The normalized sentiment score of the topic "the willingness to recommend" for a listing	0.750	0.100	0	1
Perceived value	enjoyment and pleasure	The normalized sentiment score of the topic "enjoyment and pleasure" for a listing	0.627	0.080	0	1
	value for money	The normalized sentiment score of the topic "value for money" for a listing	0.755	0.121	0	1
PE	aesthetics and comfort	The normalized sentiment score of the topic "aesthetics and comfort" for a listing	0.866	0.101	0	1
	amenities	The normalized sentiment score of the topic "amenities" for a listing	0.578	0.091	0	1
	surroundings	The normalized sentiment score of the topic "surroundings" for a listing	0.773	0.126	0	1
	location and transportation	The normalized sentiment score of the topic "location and transportation" for a listing	0.618	0.090	0	1
	safety facilities	The normalized sentiment score of the topic "safety facilities" for a listing	0.734	0.115	0	1
HI	reliability	The normalized sentiment score of the topic "reliability" for a listing	0.578	0.134	0	1
	hospitality and caring	The normalized sentiment score of the topic "hospitality and caring" for a listing	0.880	0.109	0	1
	professionalism	The normalized sentiment score of the topic "professionalism" for a listing	0.731	0.104	0	1
	social interaction	The normalized sentiment score of the topic "social interaction" for a listing	0.640	0.101	0	1

$$\begin{aligned}\text{Attitudinal loyalty}_i = {} & \beta_0+\beta_1\text{Physical environment}_i+\beta_2\text{Human interaction}_i \\ & +\beta_3\text{Price}_i+\beta_4\text{District}_i+\beta_5\text{Gender}_i+\beta_6\text{Response rate}_i \\ & +\beta_7\text{Confirmation time}_i+\beta_8\text{Acceptance rate}_i \\ & +\beta_9\text{Sales volume}_i+\beta_{10}\text{Homepage}_i+\varepsilon_i^{'} \end{aligned} \tag{2}$$

$$\begin{aligned}\text{Attitudinal loyalty}_i = {} & \delta_0+\delta_1\text{Physical Eenvironment}_i+\delta_2\text{Human interaction}_i \\ & +\delta_3\text{Perceived value}_i+\delta_4\text{Price}_i+\delta_5\text{District}_i+\delta_6\text{Gender}_i \\ & +\delta_7\text{Response rate}_i+\delta_8\text{Confirmation time}_i+\delta_9\text{Acceptance rate}_i \\ & +\delta_{10}\text{Sales volume}_i+\delta_{11}\text{Homepage}_i+{\varepsilon'}'_i \end{aligned} \tag{3}$$

$$\begin{aligned}\text{Behavioral loyalty}_i = {} & \gamma_0+\gamma_1\text{Physical environment}_i+\gamma_2\text{Human interaction}_i \\ & +\gamma_3\text{Price}_i+\gamma_4\text{District}_i+\gamma_5\text{Gender}_i+\gamma_6\text{Response rate}_i \\ & +\gamma_7\text{Confirmation time}_i+\gamma_8\text{Acceptance rate}_i \\ & +\gamma_9\text{Sales volume}_i+\gamma_{10}\text{Homepage}_i+{\varepsilon'}^{'}{}'_i \end{aligned} \tag{4}$$

$$\begin{aligned}\text{Behavioral loyalty}_i = {} & \eta_0+\eta_1\text{Physical Eenvironment}_i+\eta_2\text{Human interaction}_i \\ & +\eta_3\text{Perceived value}_i+\eta_4\text{Price}_i+\eta_5\text{District}_i+\eta_6\text{Gender}_i \\ & +\eta_7\text{Response rate}_i+\eta_8\text{Confirmation time}_i \\ & +\eta_9\text{Acceptance rate}_i+\eta_{10}\text{Sales volume}_i+\eta_{11}\text{Homepage}_i+{\varepsilon'}^{'}{}'{}'_i \end{aligned} \tag{5}$$

4. Results and analyses

4.1. The influence of customer experience on perceived value

Table 6 presents the standardized regressions for perceived value and customer loyalty. Model 1 regarding the effects of customer experience on perceived value supports Hypotheses 1a and 1b. Specifically, the perceived dimensions of the PE (α_1=0.276, p < 0.001) and HI (α_2=0.248, p < 0.001) are positively associated with perceived value. The findings are in line with previous studies arguing that host hospitality and property characteristics are distinctive features of customer experience, resulting in perceived value [27,34].

To compare the effects of HI and the PE on perceived value, we conduct the test for the difference between two standardized independent regression coefficients. Following the previous literature [54], we find that there is no substantial difference between the PE and HI in affecting perceived value ($t=\frac{\alpha_1-\alpha_2}{SE_{\alpha_1-\alpha_2}}$=(0.276–0.248)/ $\sqrt{\frac{1-0.248}{4155}[1.543+1.515-2(-0.639)]}$ $= 0.9996 < 1.96$, df = 4155, n.s.). Thus, Hypothesis 2 is not supported. Contrary to our expectation, the result has shown that the PE is as crucial as HI when making a value judgment in P2P accommodations. Some scholars have argued that customers value host hospitality and social interaction more than functional features in the accommodation-sharing economy [3,4]. Other researchers have refuted this view and argued that perceived value

Table 4
Summary statistics of key variables.

Variables	Description	Mean	S. D	Min	Max
Behavioral loyalty	The number of guests who have repeatedly purchased the same listing	1.157	2.463	0	29
Attitudinal loyalty	The average of normalized sentiment scores of the topics including "repurchase intentions" and "the willingness to recommend" extracted from online customer reviews for each listing	0.743	0.087	0.3	1
Perceived value	The average of normalized sentiment scores of the topics including "enjoyment and pleasure" and "value for money" extracted from online customer reviews for each listing	0.691	0.079	0.328	0.875
PE	The average of normalized sentiment scores of the topics including "aesthetics and comfort", "amenities", "surroundings", "location and transportation", and "safety facilities" extracted from online customer reviews for each listing	0.714	0.064	0.467	0.886
HI	The average of normalized sentiment scores of the topics including "hospitality and caring", "professionalism", "social interaction", and "reliability" extracted from online customer reviews for each listing	0.707	0.071	0.310	0.910
Price	The average price of a listing	337.578	345.745	1	7500
District	A dummy variable about whether a listing is located in one of six central districts in Beijing, including Dongcheng, Xicheng, Chaoyang, Haidian, Fengtai, and Shijingshan with values of 1 = Yes and 0 = No	0.842	0.365	0	1
Gender	The gender of a host who owns a listing with values of 0 = male and 1 = female	0.608	0.488	0	1
Response rate	The rate that a host responds to questions asked by renters	0.938	0.104	0	1
Confirmation time	The number of minutes it takes for a host to confirm the renter reservation	6.598	19.220	0	552
Acceptance rate	The acceptance rate of renter reservations	0.860	0.146	0.039	1
Sales volume	The number of historical reservations that a host has achieved	212.576	346.366	1	2115
Homepage	A dummy variable about whether a host opens an online homepage with values of 1 = Yes and 0 = No	0.240	0.427	0	1

originates more from the PE than HI [13]. Our findings support previous literature for Chinese guests who choose P2P accommodations, arguing that product attributes and fundamental needs are as prominent as social interaction and interpersonal relationships [55].

4.2. The influence of perceived value on customer loyalty

Models 3 and 5 in Table 6 demonstrate that perceived value is positively associated with customer loyalty pertaining to attitudinal loyalty (δ_3=0.172, $p < 0.001$) and behavioral loyalty (η_3=0.119, $p < 0.001$). Thus, Hypotheses 3a and 3b are supported. This confirms that the value perception of the consumption experience can result in positive brand loyalty in the attitudinal and behavioral dimensions in the service market [39].

To examine whether perceived value has a comparable relationship to attitudinal loyalty and behavioral loyalty, we adopt a "net regression" method to test this issue [54]. Two dependent variables are in the same unit because we have standardized them. We create a new dependent variable by subtracting the predicted value of behavioral loyalty (Eq. (5)) from attitudinal loyalty (Eq. (3)) and estimate the influence of perceived value on this new variable. Evidence has shown that perceived value exerts a stronger influence on attitudinal loyalty than on behavioral loyalty (β=0.052, $p < 0.001$), as illustrated in Model 6 from Table 6. In particular, the influence of perceived value on attitudinal loyalty is greater than that on behavioral loyalty. Thus, Hypothesis 4 is supported. This result supports prior literature arguing that the generation of behavioral loyalty requires more benefits than attitudinal loyalty when customers feel perceived value in purchasing the experiential product [18].

4.3. The mediating role of perceived value

To conduct the mediation analysis, we adopt Baron and Kenny's approach [56] and perform a Sobel test [57], as shown in Table 7. Perceived value acts as a mediator when it meets the following conditions: (a) the independent variables (i.e., PE and HI) significantly affect the dependent variables (i.e., attitudinal loyalty and behavioral loyalty); (b) the independent variables significantly affect perceived value; (c) perceived value significantly affects the dependent variables when the independent variables are controlled; (d) the Sobel tests are significant when examining the mediation effects. All the mediation tests demonstrate the mediating role of perceived value between customer experience (i.e., PE and HI) and customer loyalty (i.e., attitudinal loyalty and behavioral loyalty) (Z-value = 9.628, 10.007, 6.705, and 6.830, $p < 0.001$). Thus, Hypothesis 5 is supported. This finding is consistent with previous research supporting that perceived value mediates the customer experience-loyalty relationship [21].

4.4. Robustness check

To ensure the robustness of our proposed model, we perform several checks as follows. To rule out some issues caused by empirical and text analyses, we divide this robustness check into two parts. One concerns the selection of variables in the empirical study, as illustrated in Table C.

Table 5
Correlations.

(13)													1
(12)												1	0.368***
(11)											1	0.070***	0.080***
(10)										1	−0.138***	−0.069***	−0.059***
(9)									1	−0.131***	0.469***	0.079***	0.121***
(8)								1	0.014	0.004	−0.013	−0.050***	−0.099***
(7)							1	0.054***	0.044***	−0.035**	0.017	0.161***	0.106***
(6)						1	−0.047***	−0.016	−0.021	−0.007	0.003	−0.074***	0.005
(5)					1	−0.027*	0.070***	0.021	0.166***	−0.029*	0.153***	0.157***	0.117***
(4)				1	0.538***	−0.062***	0.074***	0.014	0.166***	−0.054***	0.150***	0.172***	0.115***
(3)			1	0.433***	0.416***	−0.080***	0.040**	−0.005	0.119***	−0.049***	0.114***	0.185***	0.090***
(2)		1	0.432***	0.545***	0.541***	−0.003	0.049***	0.023	0.145***	−0.048***	0.134***	0.150***	0.096***
(1)	1	0.360***	0.321***	0.374***	0.396***	−0.104***	0.044***	0.007	0.069***	−0.029*	0.113***	0.236***	0.116***
	(1) Behavioral loyalty	(2) Attitudinal loyalty	(3) Perceived value	(4) PE	(5) HI	(6) Price	(7) District	(8) Gender	(9) Response rate	(10) Confirmation time	(11) Acceptance rate	(12) Sales volume	(13) Homepage

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The other addresses the problems caused by measurement errors from text analysis, as shown in Table D. First, considering that listings volume depicting the number of listings managed by an owner may determine customer trust [7], we add the variable "Number of listings" to the original model, as shown in Models 1 and 2. Second, we transform *Price* from a continuous variable to a categorical one. Because the average price of all the samples is 337 yuan, we set the price in three dimensions: low (1 = less than 337 yuan), medium (2 = between 337 and 674), and high (3 = more than 674 yuan), as illustrated in Models 3 and 4. Third, we recalculate the sentiment score of each topic according to three typical levels of sentiment polarity: positive, negative, and neutral, as shown in Models 5 and 6. Fourth, considering the measurement errors of variables generated via data mining [58], we introduce measurement errors of 30% through human intervention by changing the sentiment polarity of 105,907 sentences randomly, as presented in Models 7 and 8. In summary, the results are consistent with our findings in the proposed model.

Because our proposed model has supported the mediating role of perceived value between customer experience and customer loyalty, perceived value may be endogenous. Following previous literature [59,60], we use two-stage least square (2SLS) regressions to correct for the endogeneity. In stage one, we regress perceived value on PE, HI, and control variables to obtain the residual free of the impact of customer experience (i.e., PE and HI), as shown in Model 1 from Table 6. The results demonstrate that PE, HI, price, and sales volume are significantly associated with perceived value ($p < 0.001$), supporting the use of the 2SLS regression to correct for potential endogeneity problems. In stage two, we use the residual as an indicator of perceived value, which refers to the portion of perceived value that was not explained by customer experience (i.e., PE and HI), to estimate attitudinal loyalty (Eq. (3)) and behavioral loyalty (Eq. (5)), as shown in Models 9 and 10 from Table E, respectively. The results are consistent with our findings, indicating the robustness of our research framework.

5. Discussions

5.1. Findings

Based on the LDA model, we extract thirteen topics, including attitudinal loyalty (i.e., "repurchase intentions" and "the willingness to recommend"), perceived value (i.e., "enjoyment and pleasure" and "value for money"), PE (i.e., "aesthetics and comfort", "amenities", "surroundings", "location and transportation", and "safety facilities"), and HI dimensions (i.e., "reliability", "hospitality and caring", "professionalism", and "social interaction"). By calling traditional machine learning classifiers to predict the topics hidden in customer reviews, we find that SVM is the optimal classifier for topic prediction. Evidence has shown that "aesthetics and comfort", "hospitality and caring", "location and transportation", and "enjoyment and pleasure" are the top four topics that Chinese guests care about. Moreover, sentiment analysis indicates that positive reviews are the majority.

After text mining, we adopt econometric models to empirically investigate the effects of customer experience, including the PE and HI, on perceived value and customer loyalty from the S-O-R perspective. Based on 4166 listings from Xiaozhu.com, we find that the PE and HI are positively associated with perceived value. Notably, the PE is as critical as HI in influencing perceived value for Chinese guests. In addition, we provide strong evidence that perceived value has a direct and positive influence on attitudinal loyalty and behavioral loyalty. Evidence has shown that the positive effect of perceived value on attitudinal loyalty is stronger than that on behavioral loyalty. Moreover, perceived value mediates the positive effects of customer experience (i.e., PE and HI) on customer loyalty (i.e., attitudinal loyalty and behavioral loyalty).

Table 6
Standardized regressions for perceived value and customer loyalty.

	Perceived value	Attitudinal loyalty		Behavioral loyalty		Attitudinal loyalty-$\widehat{Behavioral\ loyalty}$
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Perceived value			0.172***		0.119***	0.052***
			(0.014)		(0.016)	(0.014)
PE	0.276***	0.352***	0.304***	0.204***	0.171***	0.134***
	(0.016)	(0.015)	(0.015)	(0.016)	(0.017)	(0.015)
HI	0.248***	0.341***	0.299***	0.260***	0.230***	0.069***
	(0.016)	(0.015)	(0.015)	(0.016)	(0.017)	(0.015)
Price	−0.050***	0.031*	0.039**	−0.075***	−0.069***	0.108***
	(0.014)	(0.012)	(0.012)	(0.014)	(0.014)	(0.012)
District	−0.016	−0.008	−0.005	−0.018	−0.016	0.011
	(0.014)	(0.012)	(0.012)	(0.014)	(0.014)	(0.012)
Gender	−0.009	0.013	0.015	0.009	0.010	0.005
	(0.014)	(0.012)	(0.012)	(0.014)	(0.014)	(0.012)
Response rate	0.013	0.018	0.016	−0.048**	−0.049**	0.065***
	(0.015)	(0.014)	(0.014)	(0.016)	(0.016)	(0.014)
Confirmation time	−0.017	−0.012	−0.009	0.0004	0.002	−0.012
	(0.014)	(0.012)	(0.012)	(0.014)	(0.014)	(0.012)
Acceptance rate	0.020	0.017	0.013	0.054**	0.051**	−0.038**
	(0.015)	(0.014)	(0.014)	(0.016)	(0.015)	(0.014)
Sales volume	0.097***	0.037**	0.020	0.154***	0.142***	−0.122***
	(0.015)	(0.013)	(0.013)	(0.015)	(0.015)	(0.013)
Homepage	−0.010	−0.0002	0.001	0.010	0.011	−0.010
	(0.015)	(0.013)	(0.013)	(0.015)	(0.015)	(0.013)
Constant	−8.88e-08	1.34E-07 (0.012)	1.50E-07	3.85E-09 (0.014)	1.45E-08 (0.014)	1.35E-07
	(0.013)		(0.012)			(0.012)
F	137.03***	262.6***	261.82***	121.47***	117.27***	41.3***
R-squared	0.248	0.3873	0.4094	0.2262	0.237	0.0986
Mean VIF	1.20	1.20	1.23	1.20	1.23	1.23

Notes: Number of samples =4166, standard errors are in parentheses; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, +$p < 0.1$.

5.2. Theoretical and managerial implications

5.2.1. Theoretical and methodological implications

As a community-based service, the sharing economy heavily relies on WOM marketing [27]. Customer-generated content, such as online reviews, has become an important source to capture customer experience [3]. Through text analysis and an empirical study of customer experience, we provide some theoretical implications for the literature. First, the findings not only support previous studies on the customer experience-perceived value-customer loyalty path but also contribute to the current conceptualization of customer experience in Chinese P2P accommodations. Specifically, we contribute to the existing literature on customer experience by confirming that the S-O-R framework better illustrates consumer progressive psychological changes in experiential services, supporting the positive associations among customer experience, perceived value, and customer loyalty. In addition, this research answers what aspects customers pay attention to in P2P accommodations and advances knowledge of the accommodation experience by extracting and summarizing opinions from online customer reviews [9]. Specifically, basic needs (“aesthetics and comfort”), staff hospitableness (“hospitality and caring”), and location (“location and transportation”) are the salient aspects that customers care most about.

Second, this research offers evidence for explaining the subdimensions of the PE and HI and expands the theoretical contribution to the link between customer experience and perceived value for Chinese guests. The four subdimensions of HI, namely, “professionalism”, “hospitality and caring”, “reliability”, and “social interaction”, are consistent with previous literature on customer experience toward accommodations [13,26]. In addition, the five subdimensions of the PE, including “amenities”, “surroundings”, “aesthetics and comfort”, “location and transportation”, and “safety facilities”, are in line with the work of Cetin and Walls, who have found that ambiance, space/function/amenities, design, and signs/symbols/artifacts are the themes of the PE dimension [26]. Notably, we add new insights into cultural differences in service businesses by showing that the PE is as important as HI among Chinese guests when making a value judgment about a product. Previous literature that has exclusively focused on Western societies when investigating customer experience in P2P accommodations has found that HI is crucial to determining customer behavior [27,28]. In contrast, our research offers empirical evidence that enriches the understanding of the Chinese guest experience. Our findings not only emphasize the same importance of physical experience and social interaction in the accommodation-sharing economy [27,34] but also explain that in Eastern culture, Chinese guests greatly appreciate the collective warmth from service providers as well as the utility and function of products [55].

Another theoretical contribution of this study is the simultaneous consideration of attitudinal loyalty and behavioral loyalty. A large body of literature has focused on examining the antecedents of customer loyalty, yet there is limited literature on behavioral loyalty [14,26]. This research advances knowledge of behavioral loyalty and supports the positive customer experience-perceived value-customer loyalty relationship. Moreover, we have provided evidence that perceived value has a comparable relationship to attitudinal loyalty and behavioral loyalty, confirming previous findings that behavioral loyalty requires more resources than attitudinal loyalty after customers obtain perceived value [18].

Finally, this study provides a methodological contribution on how to deal with unstructured Chinese text using multiple methods by employing the LDA model, machine learning algorithms, and dictionaries to extract topics and summarize topic-specific sentiments and combining text mining with econometric analysis to determine the causal relationship between extracted opinions. Previous studies have examined customer experience from the English text by using hierarchical cluster analysis and qualitative content analysis [8,28], ignoring the relationship between extracted customer opinions [3,27]. In this study, we calculate topic-specific sentiment based on grammatical rules using stopwords and dictionaries because the Chinese language is relatively complex. To conduct an in-depth investigation to understand customer experience, we not only capture the topics that customers are concerned about but also make a performance assessment of customer experience for each product. More importantly, we deeply gauge the

Table 7
Mediation tests of perceived value.

HI-Perceived value-Attitudinal loyalty	HI	Perceived value
Model 2 (Dependent variable: Attitudinal loyalty)	0.341*** (0.015)	
Model 1 (Dependent variable: Perceived value)	0.248*** (0.016)	
Model 3 (Dependent variable: Attitudinal loyalty)	0.299*** (0.015)	0.172*** (0.014)
Sobel test *Z*-value: $0.248 \times 0.172/\sqrt{0.248^2 \times 0.014^2 + 0.172^2 \times 0.016^2} = 9.628$, $p < 0.001$		
PE-Perceived value-Attitudinal loyalty	PE	Perceived value
Model 2 (Dependent variable: Attitudinal loyalty)	0.352*** (0.015)	
Model 1 (Dependent variable: Perceived value)	0.276*** (0.016)	
Model 3 (Dependent variable: Attitudinal loyalty)	0.304*** (0.015)	0.172*** (0.014)
Sobel test *Z*-value: $0.276 \times 0.172/\sqrt{0.276^2 \times 0.014^2 + 0.172^2 \times 0.016^2} = 10.007$, $p < 0.001$		
HI-Perceived value-Behavioral loyalty	HI	Perceived value
Model 4 (Dependent variable: Behavioral loyalty)	0.260*** (0.016)	
Model 1 (Dependent variable: Perceived value)	0.248*** (0.016)	
Model 5 (Dependent variable: Behavioral loyalty)	0.230*** (0.017)	0.119*** (0.016)
Sobel test Z-value: $0.248 \times 0.119/\sqrt{0.248^2 \times 0.016^2 + 0.119^2 \times 0.016^2}$=6.705, $p < 0.001$		
PE-Perceived value-Behavioral loyalty	PE	Perceived value
Model 4 (Dependent variable: Behavioral loyalty)	0.204*** (0.016)	
Model 1 (Dependent variable: Perceived value)	0.276*** (0.016)	
Model 5 (Dependent variable: Behavioral loyalty)	0.171*** (0.017)	0.119*** (0.016)
Sobel test Z-value: $0.276 \times 0.119/\sqrt{0.276^2 \times 0.016^2 + 0.119^2 \times 0.016^2} = 6.830$, $p < 0.001$		

Notes: standard errors are in parentheses; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, +$p < 0.1$.

formation mechanisms of customers' psychological process after purchasing and uncover the consequences of customer experience by extracting the relationship between extracted customer opinions. This can help scholars understand customer experience and its subsequent outcomes in the Chinese market by analyzing online customer reviews using a combination of qualitative and quantitative approaches.

5.2.2. Managerial implications

Based on our findings, we can provide some suggestions for service providers to formulate service operation strategies. On the one hand, to satisfy customers' needs, it is necessary to improve the customer experience by creating a harmonious physical environment and enhancing human interaction. For instance, service providers can create a home-like atmosphere by designing and arranging living accommodations. In addition, we suggest that they address customers' interest in convenience and safety by offering cooking utensils and installing a security door. Moreover, service providers should try their best to build a warm host-guest relationship by creating harmonious communications and offering high-quality service. It is also helpful for service providers to gain customers by providing a greeting, showing a smiling face, and caring about customer needs. More broadly, these suggestions apply not only to P2P accommodations but also to other service businesses. In the experiential industry, to retain customers to create profits, service providers should optimize the atmosphere of HI and improve the sensory experience of the PE to increase customers' perceived value.

We also provide suggestions for market supervisors to enhance user-friendly interface design according to customer experience extracted from online reviews and optimize service delivery systems by regulating the sharing economy. Considering the salient attributes that customers care most about, platform designers can summarize customer opinions and label them in eye-catching positions from the aspects of the PE and HI. In particular, room decorations (e.g., "aesthetics and comfort"), hospitality (e.g., "hospitality and caring"), and sociality (e.g., "social interaction") can be added to the rating aspects. Moreover, it is suggested that market operators should pay attention to regulating service quality (e.g., human interaction) as well as product quality (e.g., physical environment) in the sharing economy. Given that service providers may not receive the same professional training as traditional service industries, managers should improve the professionalism of personnel through vocational training to attract and retain customers [27]. Specifically, market managers should set up standard procedures to optimize the servitization of service providers, particularly in terms of their responsibility for personal safety and issues of deposit refunds in service businesses. Moreover, market managers should supervise the physical environment and encourage service providers to passionately interact with customers to energize the sharing economy by attracting potential customers and retaining existing customers.

5.3. Limitations and future directions

There are some limitations of this work that need future research attention. First, we obtained data only from Xiaozhu.com in Beijing. Caution should be exercised in other cities, such as Shanghai and Guangzhou, where customers may value various service or product attributes. Second, considering that perceived value can be divided into utilitarian and hedonic value, future research can also examine the antecedents and consequences of different kinds of customer value. Third, focusing on products with customer reviews can lead to sample selection bias, as a product may have no reviews on online platforms. Using lab experiments helps provide supplementary evidence for interpreting customer experience and avoiding sample selection bias through simulating purchasing scenarios in P2P accommodations. Fourth, due to the measurements of variables of interest derived from topic-specific sentiment implied in customer reviews, our proposed model cannot be tested as a system of regressions using structural equation modeling (SEM). Survey data can be added as an additional analysis to repeat the proposed model and give simultaneous estimations of equations in future research.

6. Conclusion

This research deepens our understanding of customer experience in the sharing economy by uncovering the subdimensions of HI and the PE. Our findings support the positive customer experience-perceived value-customer loyalty link. Moreover, we demonstrate no substantial difference between the PE and HI in affecting perceived value for Chinese guests. In addition, we find that the positive effect of perceived value on attitudinal loyalty is stronger than that on behavioral loyalty.

By integrating customer experience and perceived value as well as customer loyalty into the S-O-R model, our study answers several questions about the direct and indirect consequences of customer experience in terms of the PE and HI. It not only offers new insights into the sharing economy and potentially into the experiential industry but also provides a theoretical perspective on the customer behavior literature by simultaneously considering attitudinal loyalty and behavioral loyalty. In addition, we employ a mixed-methods approach using LDA and machine learning algorithms to capture essential signals from online customer reviews and then combine data mining with econometric analyses to gauge customers' psychological and behavioral changes when encountering environmental stimuli. We hope that our study provides a methodological perspective for research on addressing unstructured data, such as provider self-descriptions.

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Declaration of Competing Interest

None.

Appendix A. Appendix

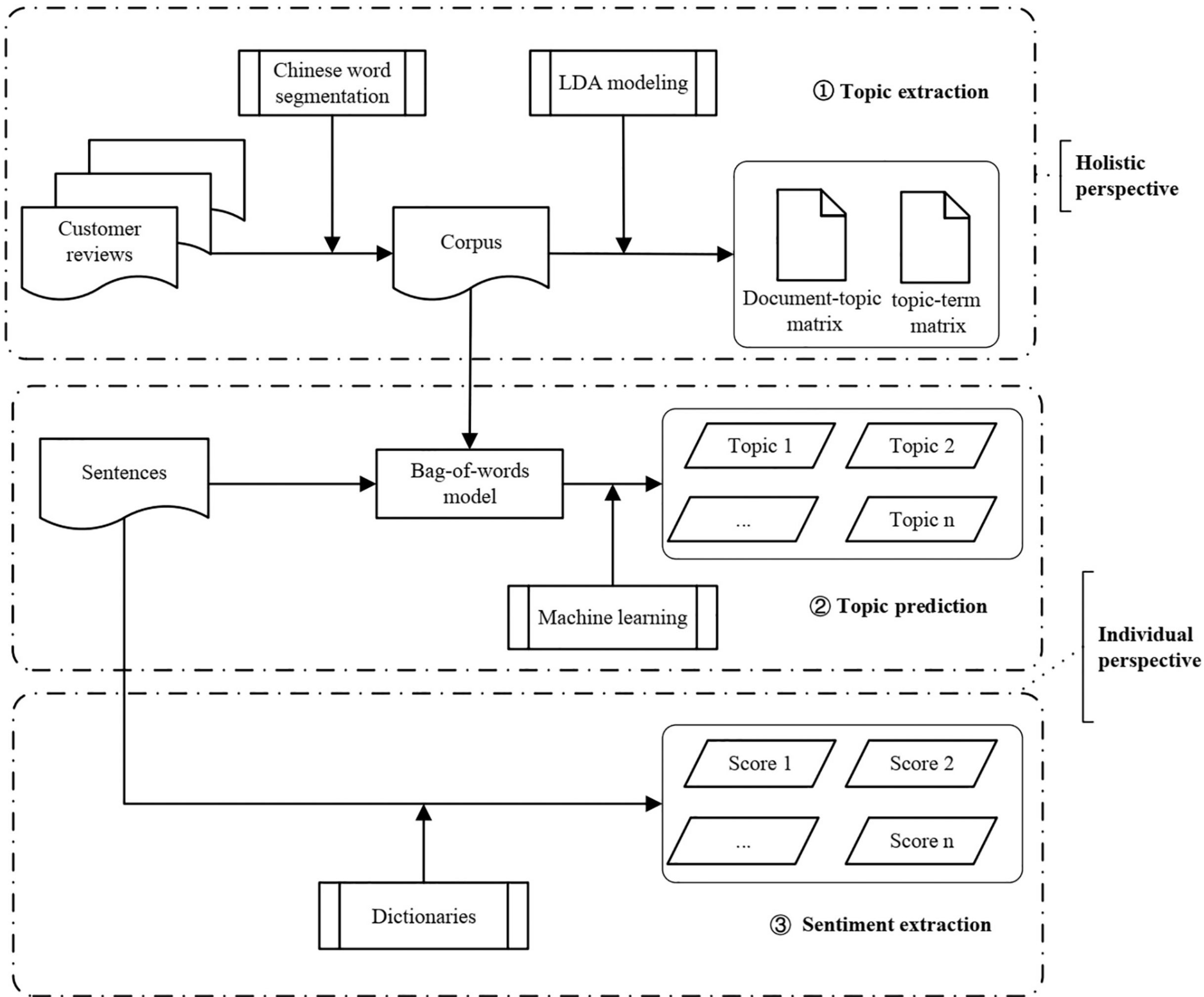

Fig. A. Three steps of text analyses.

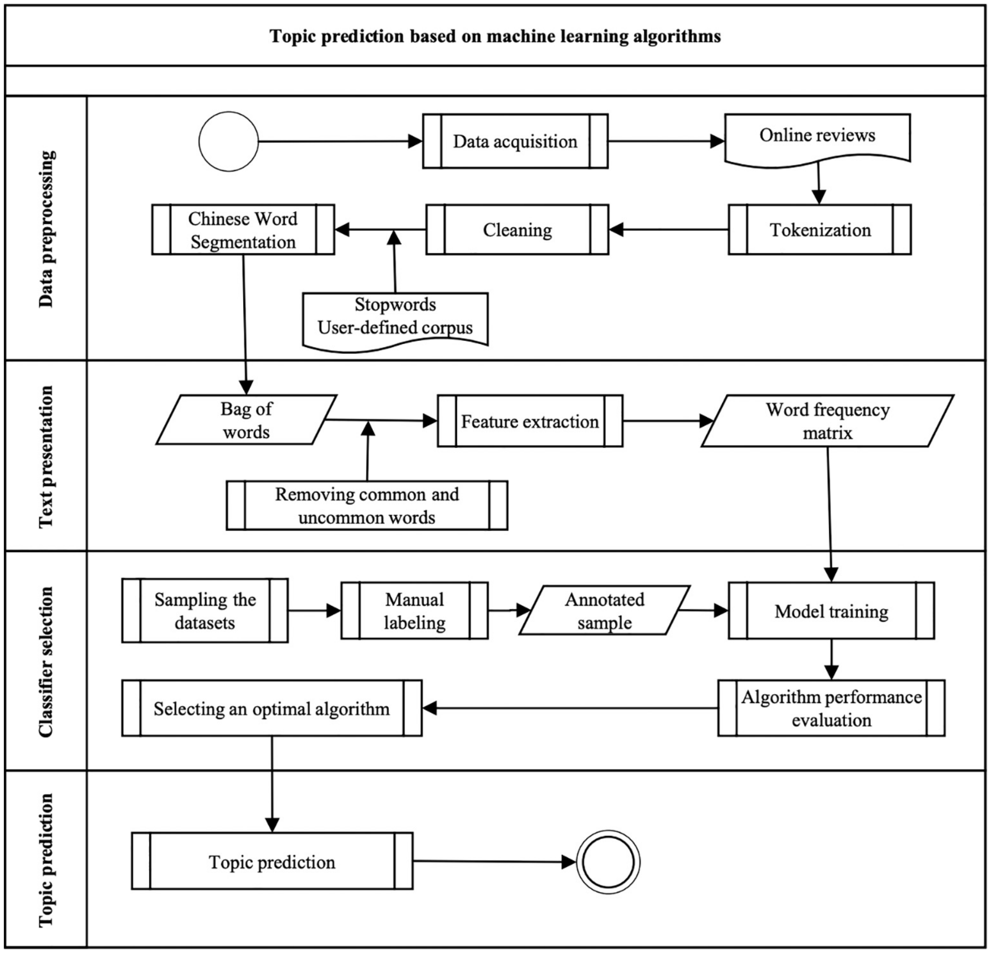

Fig. B. Procedures for topic prediction.

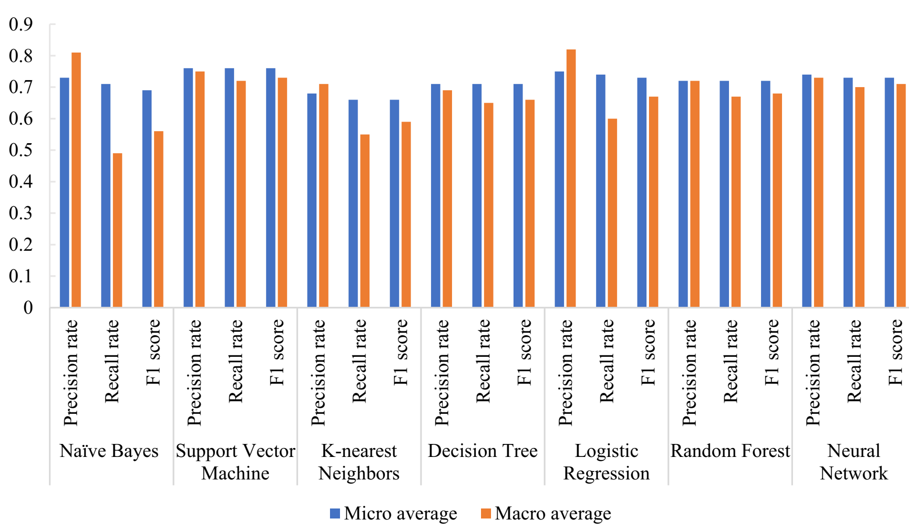

Fig. C. Performance indicators of several classifiers.

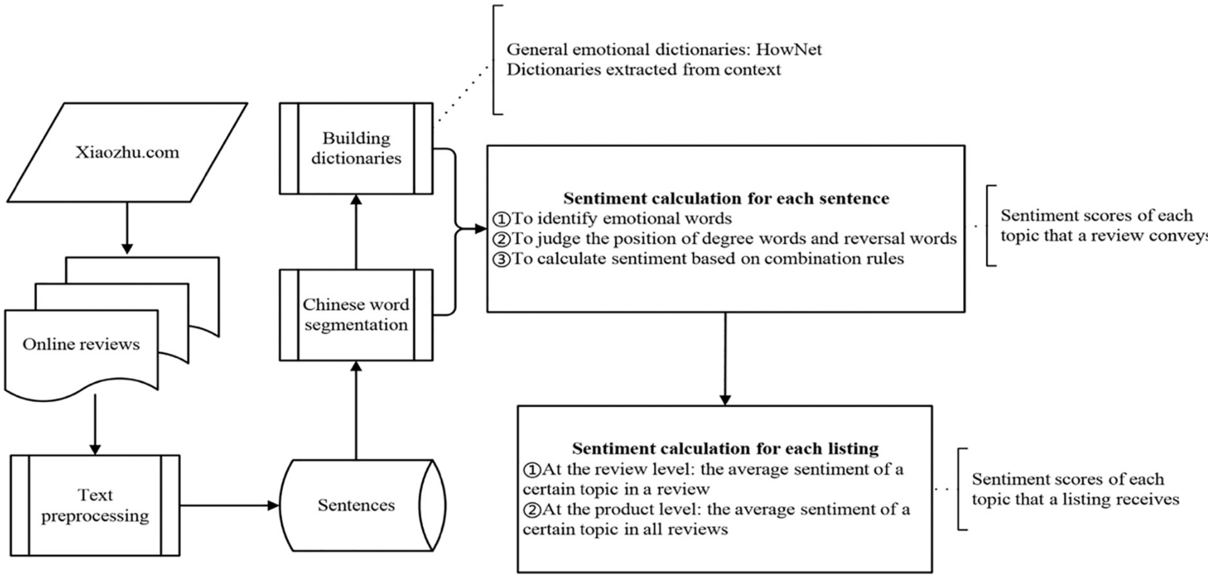

Fig. D. Sentiment analysis.

Table A
Data preprocessing.

Data preprocessing	Description
Data acquisition	Texts are crawled from customer reviews in an online short-term rental using Python.
Tokenization	Text is broken into words using Jieba
Cleaning	Pinyin is converted to words, and words composed of unknown symbols are removed.
Spelling	Words with spelling mistakes are modified.
Keeping user-defined words	Fixed words are not cut by Chinese word segmentation (Jieba) but kept.
Removing stopwords	Common words and uncommon words appeared once are removed.

Table B
Manual labeling for sentences.

Dimensions	Topics	Sentences
Customer loyalty	repurchase intentions	I will definitely come here again if I have a chance.
	the willingness to recommend	I hope that more travelers will come here in the future.
Perceived value	enjoyment and pleasure	Overall, I feel good and satisfied.
	value for money	It is a cheap and suitable accommodation for the first time.
PE	aesthetics and comfort	This bed is very comfortable
	amenities	The house is fully equipped.
	surroundings	Everything is around
	location and transportation	The transportation is convenient.
	safety facilities	Don't worry about safety.
HI	reliability	The situation at home is the same as the photo shows.
	hospitality and caring	The landlord is very enthusiastic.
	professionalism	Any problems will be solved promptly.
	social interaction	The shared tenants are very friendly

Table C
Robustness check of several tests for variables selection in the empirical study.

Variables	Attitudinal loyalty	Behavioral loyalty	Attitudinal loyalty	Behavioral loyalty
	Model 1	Model 2	Model 3	Model 4
Perceived value	0.168***(0.014)	0.111***(0.015)	0.174***(0.014)	0.119***(0.016)
PE	0.298***(0.015)	0.158***(0.017)	0.305***(0.015)	0.171***(0.017)
HI	0.287***(0.015)	0.206***(0.017)	0.300***(0.015)	0.228***(0.017)
Price	0.042**(0.012)	−0.063***(0.014)		
District	−0.002(0.012)	−0.009(0.014)	−0.010(0.012)	−0.010(0.014)
Gender	0.012(0.012)	0.004(0.014)	0.013(0.012)	0.012(0.014)

(*continued on next page*)

Table C (*continued*)

Variables	Attitudinal loyalty	Behavioral loyalty	Attitudinal loyalty	Behavioral loyalty
	Model 1	Model 2	Model 3	Model 4
Response rate	0.016(0.014)	−0.047**(0.015)	0.015(0.014)	−0.048**(0.016)
Confirmation time	−0.012(0.012)	−0.004(0.014)	−0.009(0.012)	0.003(0.014)
Acceptance rate	0.017(0.014)	0.061***(0.015)	0.011(0.014)	0.053**(0.016)
Sales volume	0.048**(0.014)	0.203***(0.016)	0.021(0.013)	0.143***(0.015)
Homepage	0.021(0.014)	0.053***(0.015)	0.0001(0.013)	0.012(0.015)
Number of listings	−0.073***(0.014)	−0.157***(0.016)		
Price level			0.057***(0.012)	−0.063***(0.014)
Constant	1.46E-07(0.012)	6.91E-09(0.013)	1.44E-07(0.012)	2.19E-08(0.014)
F	243.55***	117.72***	263.64***	116.75***
R-squared	0.4131	0.2538	0.4111	0.2361
Mean VIF	1.28	1.28	1.23	1.23

Notes: Number of samples =4166, standard errors are in parentheses; ***p < 0.001, **p < 0.01, *p < 0.05, +p < 0.1.

Table D
Robustness check of several tests for measurement errors in text analysis.

Variables	Attitudinal loyalty	Behavioral loyalty	Attitudinal loyalty	Behavioral loyalty
	Model 5	Model 6	Model 7	Model 8
Perceived value	0.173***(0.014)	0.108***(0.016)	0.111***(0.015)	0.086***(0.015)
PE	0.323***(0.015)	0.157***(0.018)	0.091***(0.015)	0.065***(0.015)
HI	0.310***(0.015)	0.259***(0.017)	0.131***(0.015)	0.104***(0.015)
Price	0.037**(0.011)	−0.069***(0.014)	0.054***(0.015)	−0.090***(0.015)
District	−0.015(0.012)	−0.021(0.014)	0.024(0.015)	−0.007(0.015)
Gender	0.010(0.011)	0.007(0.014)	−0.016(0.015)	0.022(0.015)
Response rate	0.016(0.013)	−0.051**(0.015)	0.045**(0.017)	−0.004(0.017)
Confirmation time	−0.001(0.012)	0.007(0.014)	0.0003(0.015)	−0.001(0.015)
Acceptance rate	0.006(0.013)	0.048**(0.015)	0.013(0.017)	0.087***(0.017)
Sales volume	0.012(0.013)	0.137***(0.015)	0.043**(0.016)	0.202***(0.016)
Homepage	0.010(0.012)	0.009(0.015)	−0.002(0.016)	0.032*(0.016)
Constant	1.55E-07(0.011)	−2.84E-10(0.013)	−2.13E-07(0.015)	−2.67E-08(0.015)
F	323.38***	124.89***	21.04***	40.77***
R-squared	0.4613	0.2485	0.0528	0.0974
Mean VIF	1.27	1.27	1.10	1.10

Notes: Number of samples =4166, standard errors are in parentheses; ****p* < 0.001, ***p* < 0.01, **p* < 0.05, +*p* < 0.1.

Table E
Stage two from 2SLS standardized regression results of customer loyalty.

Variables	Attitudinal loyalty	Behavioral loyalty
	Model 9	Model 10
Perceived value	0.172***(0.014)	0.119***(0.016)
PE	0.352***(0.014)	0.204***(0.016)
HI	0.341***(0.014)	0.260***(0.016)
Price	0.031*(0.012)	−0.075***(0.014)
District	−0.008(0.012)	−0.018(0.014)
Gender	0.013(0.012)	0.009(0.014)
Response rate	0.018(0.014)	−0.048**(0.016)
Confirmation time	−0.012(0.012)	0.0004(0.014)
Acceptance rate	0.017(0.014)	0.054**(0.015)
Sales volume	0.037(0.013)	0.154***(0.015)
Homepage	−0.0002(0.013)	0.010(0.015)
Constant	1.34E-07(0.012)	3.91E-09(0.014)
F	261.82***	117.27***
R-squared	0.4094	0.237
Mean VIF	1.18	1.18

Notes: Number of samples =4166, standard errors are in parentheses; ***p < 0.001, **p < 0.01, *p < 0.05, +p < 0.1.

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