A Comparative Study on the Sentimental Characteristics of Chinese and Western Tourists

The research attempts to investigate the effect of cultural differences on online Airbnb reviews. The study collects 133,419 English reviews and 62,285 Chinese reviews on Airbnb website in Hong Kong. The differences between Chinese-speaking and English-speaking tourists were compared by identifying the attributes highlighted in the reviews and measuring perceptions of those attributes. The results highlight the differences between two groups of tourists in terms of the attributes they pay attention to when choosing a house of Airbnb in "host", "accommodation", "location" and "price". Additionally, the results suggest tourists speaking Chinese are generally more positive and objective when writing online reviews. Specifically, they have more a positive perception with the "host", but they are pickier about "accommodation", "location" and "price". Through text mining and sentiment analysis, our study can help Airbnb practitioners to listen to the voice of consumers and improve their marketing strategies and methods for consumers with different cultural backgrounds.

Keywords: cultural difference; Airbnb attribute; sentiment analysis;

Introduction

The sharing economy has gained popularity in the past few years, and Airbnb has become a viable alternative to traditional hotels for tourists. Airbnb has a price advantage over traditional hotels (Fang, Ye, & Law, 2016) and provides different experiences for tourists (Li et al., 2017). Therefore, Airbnb is popular with tourists and has a significant impact on the traditional hotel industry (Liu & Mattila, 2017). Hospitality scholars are increasingly concerned about the rise of Airbnb, including its degree of risk (Chang & Wang, 2018), price strategies (Lawani, Reed, Mark, Zheng, 2018; Wang & Nicolau, 2017), advertising appeals (Liu & Mattila, 2017), impact on labour (Fang et al., 2016), economic impact (Guttentag, 2015; Zervas, Proserpio, & Byers, 2014), potential discrimination (Edelman & Luca, 2014), regulatory issues (Koopman et al., 2015), online reputation (Zervas, Proserpio, & Byers, 2015), Airbnb user behavior and experiences (Tussyadiah, 2016) and the users' perceptions (Cheng & Jin, 2019). In recent studies, some scholars have focused on Airbnb's online reviews to determine what tourists care about (Cheng & Jin, 2019). Online views have become even more important recently in the field of tourism consumption because tourists can determine the product quality through reviews and comments posted online by previous consumers before making a decision (Tu & Wu, 2019; Stamolampros, Korfiatis, Symitsi & Kourouthanassis, 2018). Since Airbnb services are purchased at a distance, online reviews have become increasingly important (Viglia et al., 2016) because it is difficult for tourists to determine the quality of the Airbnb services beforehand (Klein, 1998). Airbnb is operating on the global market, and tourists from different regions have different travel preferences and consumption habits (Mooij & Beniflah, 2016). Some scholars attributed these differences to cultural differences (Forgas et al., 2012; Nakayama & Wan, 2018), including values, beliefs, and norms, and have distinguished different cultural groups (Pizam, Pine, Mok & Shin, 1997). Tourists from different regions have unique cultural backgrounds and have been exposed to various values and norms since childhood (Hofstede, 1991), and this phenomenon was observed in China and internationally (Crotts & Erdmann, 2000). Culture provides a normative framework with a range of socially acceptable behaviors, and its key function is to adjust emotional responses, expressions, and behaviors in different situations to maintain social order (Paul et al., 2017).

Online reviews provide insights into different cultures in international marketing research (Akdeniz & Talay 2013) and represent particular areas of the consumer's cultural background (Alden, Merz & He 2008). Although many studies have been conducted on Airbnb online reviews (Cheng & Jin, 2019; Lawani et al., 2018; Hoffen et al., 2017; Bridges & Vasquez 2016), few have focused on the impact of culture on the content of experienced reviewers of Airbnb. Therefore, in this study, we compare reviews of Airbnb conducted by tourists from two distinct cultures to address this research gap and determine if cultural differences can be determined by comparing the reviews (Hofstede, 2001). Tourists' online reviews involve many attributes of Airbnb (Cheng & Jin, 2019). Although more and more scholars have considered the influence of Airbnb attributes on tourists' experience, most of them focus on the concept recognition at the macro level (Tussyadiah & Zach, 2016; Guttentag, 2015; Bridges & Vasquez, 2016; Festila & Muller, 2017; Yannopoulou, 2013). Thus, this study attempts to pay attention to the nuances of Airbnb experience. Specifically, we try to find these attributes through text mining and perform sentiment analysis of text to evaluate opinions and attitudes in content (Liu & Jian, 2018).

We use Hofstede's framework (Hofstede, 1980) and a theoretical summary of the effect of cultural differences provided by Schuckert, Liu & Law (2015) to take up the suggestion by Tussyadiah and Zach's (2016) to use sentiment analysis to identify positive and negative opinions of Airbnb users. The objective is to contribute to the debate on Airbnb user experiences. We use the "fightin' words" algorithm to identify key attributes used by Airbnb reviewers and describe the reviewers' sentiments. It therefore avoids where possible pre-figuring theories and hypotheses about the possible experience (Goddard & Melville, 2001). We summarize the attributes of hotels reported in the literature and use this information as a frame of reference to understand the similarities and differences between the attributes of Airbnb and hotels. This study contributes to the sharing economy and hospitality and cross-cultural literature by providing an understanding of the Airbnb user experience of tourists from different cultures. In terms of methodology, we demonstrate how big data can be used and visualized in tourism and hospitality research to increase our understanding of tourist diversity. The findings of this study may be of interest not only to tourism management scholars but also to hoteliers who are interested in marketing campaigns tailored to different cultural segments to minimize culture shock to consumers. The results also provide guidance to Airbnb hosts to improve their marketing strategies and to tourists from different cultures.

Literature Review

Online Reviews and Airbnb attributes

Online reviews are becoming increasingly important as customers provide feedback after a consumer experience; they are fast, up-to-date, are available anywhere, and have become a word-of-mouth (WOM) marketing strategy in the digital age (Kaplan & Haenlein, 2010). From the perspective of potential customers, these reviews are one of the most readily available, trustworthy, and useful sources of information; as a result, online reviews have become the focus of scholars and other professionals. Online reviews are informal posts without a standard format; they do not have the same authority or credibility as expert opinions and face-to-face WOM, but they do provide broad product coverage and diverse opinions (Chik & Vásquez, 2017). Compared with numerical scores, online reviews better reflect true feelings and are used and trusted by potential consumers (Nakayama & Wan, 2018). Online reviews of Airbnb primarily refer to experiences related to the accommodation and are provided voluntarily by tourists. Since it is difficult for tourists to evaluate the Airbnb service before their stay, online reviews are particularly important to attract potential consumers (Radojević, Stanisic, Stanic, & Davidson, 2018). Unlike specific products, the services provided by Airbnb are intangible, and the information (e.g., company websites and advertising) provided by marketers is often considered to be biased, which makes it risky for tourists to make purchase services from

Airbnb (Nath, Devlin & Reid, 2018). Previous studies on Airbnb evaluations have mostly focused on the star rating system, and it was suggested that studies on reviews should not only rely on the ratings but instead examine the content of reviews (Bridges & Vásquez, 2016). In other words, it is necessary to consider the information in the reviews and the associated sentiment. Online platforms play an important role in attracting tourists to post and share good or bad experiences (Zhong, Leung, Law & Wu, 2013). In addition, the voluntary posting of online reviews by tourists not only provides free information to assist other tourists in their decision-making process but also helps Airbnb practitioners better understand tourists, which is important to respond rapidly to the tourists' needs and plan marketing strategies.

Airbnb's online reviews have several attributes; therefore, it is particularly important to understand the attributes of Airbnb that influence the tourists' preferences and satisfaction in the reviews. Previous studies reported different orders of importance of the attributes of Airbnb. Some scholars regarded the social interaction between guests and hosts as the core of the Airbnb experience (Lampinen & Cheshire, 2016; Tussyadiah & Pesonen, 2016; Yannopoulou, 2013), whereas some scholars have found that Airbnb users attach great importance to practical attributes, while attributes related to the experience of the stay were less important (Guttentag, 2016). In contrast, Tussyadiah (2016) found that "enjoyment" was the most important attribute. These contradictory conclusions may be due to the lack of Airbnb accommodation standards (Tussyadiah & Zach, 2016) and clear standards for the determination of Airbnb attributes. Despite various controversies, previous studies have generally included the following attributes (Tussyadiah & Zach, 2016; Guttentag, 2015; Bridges & Vasquez, 2016; Festila & Muller, 2017; Yannopoulou, 2013): location, facilities, cleanliness, authentic experience, host-guest interaction, and time spent in the local neighborhoods. However, most studies did not provide a detailed definition of these attributes. Therefore, in this study, we use text mining to obtain useful and detailed information from the large volume of online reviews. Online reviews have several attractive advantages over other types of information. First, they capture the experiences of tourists staying at Airbnb accommodations. Second, the reviews provide access to a large number of visitors, which minimizes the research effort and cost to obtain information through other channels. Third, the reviews provide quantitative and qualitative information, evaluate specific aspects, and describe the overall experience of Airbnb users. Therefore, online reviews are the primary information source to evaluate the management and marketing strategy of Airbnb.

Culture and language

An increasing number of tourists refer to opinions expressed on the Internet before making final decisions, and inherent factors such as culture may affect the expectations and evaluation of individuals (Stamolampros et al., 2018). Against the background of globalization, tourism is developing rapidly, and it is necessary to explore the influence of culture on tourism (Kang & Moscardo, 2006). It is important to understand the differences in the behavior of tourists attributed to different cultural backgrounds because the norms, values, and characteristics differ for people from different cultural groups (Eisingerich & Rubera, 2010). Eastern and Western cultures are interacting more frequently, and this has attracted the attention of marketers and scholars. Different cultural backgrounds will lead to different cognitive processes and behaviors (Lalwani & Shavitt, 2013), thereby affecting the experiences of tourists (Kumar & Pansari, 2016). In this regard, Hofstede's cultural dimensions provide a theoretical background for analyzing the influence of cultural differences on the behavior of tourists. Hofstede (1980, 1991, 2001, in press) proposed five dimensions for cultural comparison: individualism-collectivism, power distance, masculinity-femininity, uncertainty avoidance, and longterm orientation. Hofstede's cultural dimension is widely recognized and used and has proven to be universal and representative for the comparison of cultural characteristics (Kim, Jun & Kim, 2018). Hofstede (1980) emphasized the influence of the national cultural value system on individual thinking, emotions, and behavior patterns. In particular, cultural differences between visitors from different countries lead to differences in the way they think and behave and evaluate the services they receive.

Language is the external expression of culture and can be used to identify the preferences of tourists from different cultural backgrounds (Antonio et al., 2018). Online reviews based on language help us understand the attitudes and behaviors of tourists (Baker & Kim, 2019), which is crucial for Airbnb hosts. Studies have shown that English is the most widely used language in the world; most English speakers have similar cultures and customs and differ significantly from non-English speakers (Schuckert et al., 2015). A high proportion of English-speaking tourists are Western tourists, such as Americans and Europeans, and a high proportion of non-English-speaking tourists are Asian tourists, such as Chinese (Schuckert et al., 2015). Since geographical boundaries are not necessarily identical to linguistic boundaries, we believe that this differentiation is a valid approach. Online reviews may reflect the norms of the tourists, which are based on their national culture and are defined by national, racial, religious, and other boundaries (Hannerz, 1996). Although people who speak the same language are not necessarily native speakers, they may be influenced by the culture behind the language (Schuckert et al., 2015). When people use a foreign language, they not only change the language usage pattern but they are also influenced by the culture of that language (Fishman, 1968), which explains why some Japanese living in London may be more influenced by Western culture than Eastern culture if they prefer to use English. Therefore, the use of language reflects the underlying culture (Duranti, 2003). To sum up, since the subjects of this study are Chinese-speaking tourists and English-speaking tourists, according to Schuckert et al. (2015), the online reviews are divided into English reviews representing Western culture and Chinese reviews representing Eastern culture, i.e., the reviews are categorized based on language.

Differences in the emphasis

Schuckert et al. (2015) conducted a a theoretical summary on cultural differences and focused on four areas: differences in the emphasis, expectation, perception, and complaints. The emphasis refers to the importance that tourists place on various attributes. In previous studies on hotel management, researchers determined whether tourists from different cultures placed different emphasis on different attributes of hotels. Although some scholars have conducted studies on this topic (Francesco & Roberta, 2019), different conclusions were obtained. In early studies, researchers found no differences in the emphasis between eastern and western tourists (McCleary & Choi, 1998). Subsequently, researchers proposed the opposite view that significant differences exist in the emphasis between tourists from different cultures (Poon & Lock, 2005). For example, it was found that Asian tourists placed more importance on price, whereas western tourists were concerned with the appearance of the hotel. Other researchers found that the Japanese placed high emphasis on the price and the environment, whereas western tourists focused on the quality of service (Nakayama & Wan, 2018). In a study on the attitude towards waiters, Tsang and Ap (2007) found that Asian tourists were concerned with the ability of hotel waiters, while western tourists placed more emphasis on the waiters' attitudes. However, Kuo (2007) found that American tourists focused more on the ability of hotel waiters, whereas Chinese tourists were more interested in their manners. Some scholars have also found that Chinese tourists placed greater emphasis on the convenience of checking in and out of hotels. In contrast, western tourists had a greater interest in the hotel's sports facilities and in the ability of upgrading rooms (Nakayama & Wan, 2018). Although previous studies provided different conclusions, most studies are in agreement that tourists from different cultural backgrounds have different accommodation demands. Since the Airbnb service is different from traditional hotel services, the results are different from that of hotel research. For example, Belarmino et al. (2017) found that Airbnb users were interested in spontaneous interactions and local experiences, whereas hotel guests valued the facilities and room service. A survey of customers who stayed in Airbnb or hotel accommodations found that Airbnb accommodations were rated higher than hotels in terms of accommodation experience due to the ability to enjoy spontaneous interactions and local events in the community and personalize the experience (Mody, Suess, & Lehto, 2017). Since online reviews focus on different attributes (Bagheri, Saraee, & Jong, 2013), scholars have used these reviews to investigate the Airbnb experience and determine the interests of tourists. Cheng and Jin (2019) only analyzed English reviews and did not focus on the effects of cultural differences on the emphasis of users from different language groups. Therefore, in this study, we use the approach of researchers (Chen & Jin; Tussyadiah & Zach, 2016; Guttentag, 2015; Bridges & Vasquez, 2016; Festila & Muller, 2017; Yannopoulou, 2013) in recent studies on Airbnb accommodations and focus on three aspects, i.e., the host, accommodation, and location. We pose the following research questions:

RQ1: Do Chinese-speaking and English-speaking tourists place different emphasis on the host, accommodation, and location aspects of Airbnb?

RQ2: Which attributes do the tourists focus on for each aspect?

Differences in perception

Perception difference is one of the four focus areas that Schuckert et al. (2015) considered in the review of the cultural differences of tourists. The term refers to the fact that people have different perceptions of the same product or service. Cultural differences result in significantly different perceptions of the quality of services, the willingness to repeat purchases, and how the services are recommended to others (Legohérel, Daucé & Hsu,. 2012). Weiermair (2000) believed that tourists from different cultures had significantly different perceptions of the same service. Many scholars (e.g., Francesco & Roberta, 2019; Nakayama & Wan, 2018; Hsieh & Tsai, 2009; Reisinger& Turner, 1999) confirmed this result in studies of hotels and restaurants. Some scholars stated that Asian tourists provided less favorable reviews of the same service than western tourists (Hsu & Kang, 2003; Tsang & Ap, 2007; Kuo, 2007; Manrai & Manrai, 2011). The individual-collectivism and power distance described in Hofstede's framework (Hofstede, 1980) were cited as the reasons for the differences. For instance, compared with western tourists that come from an individualistic culture, Asian tourists with a collectivist culture are more likely to expect politeness and consideration. From the perspective of the power distance, some scholars believe that due to the significant power gap between Asian culture and western culture, Asian tourists are more likely to think that they are more powerful than the service providers. However, other scholars have drawn the opposite conclusion. For example, Zhang, Beatty, & Walsh (2008) found that individuals in an individualistic society, such as American tourists and European tourists, have higher expectations for services. Therefore, compared with Asian tourists, they may be less satisfied with the same services and are more rigorous in their service evaluation. Western tourists are more likely to complain than Asian tourists. For instance, Japanese tourists are more tolerant of inferior services than US tourists (Laroche, Ueltschy, Abe, Cleveland, & Yannopoulos, 2004). Nakayama and Wan (2018) found similar results. Again, although previous studies showed different results regarding hotels, most studies found that tourists from different cultural backgrounds had different perceptions of the same accommodation service. Therefore, we conjecture that the cultural background plays a vital role in shaping the tourists' perceptions of Airbnb attributes. In this regard, we pose the following research questions:

RQ3: Do Chinese-speaking and English-speaking tourists have different perceptions of the host, accommodation, and location aspects of Airbnb?

RQ4：Which attributes are perceived differently?

Research methodology

Data collection

Airbnb accommodations in Hong Kong were used as the data source in this study for the following reasons. First, Hong Kong is one of the most distinctive cities in China. In 2018, about 65.15 million people visited Hong Kong and overnight visitor arrivals were 29.26 million. By the first half of 2019, the overnight visitor arrivals were 19.95 million (Hong Kong Tourism Board, 2019). In 2016, Hong Kong surpassed London as the most visited international tourist city (Geetha, Singha & Sinha, 2017). With a large number of Chinese tourists and western tourists, Hong Kong is a multicultural tourist city, providing an excellent study area. Second, Airbnb is the most successful peer-to-peer model in the hospitality industry and has more than 7 million houses in 220 countries (Airbnb, 2020). Reviews in Chinese, English, and other languages are provided on the Airbnb website in the same format and with the same functions, allowing for easy comparison of the reviews. We collected 240484 reviews from 10970 listings in the Hong Kong portion of the Airbnb website up to June 12, 2019. We used TextBlob, a Python library for processing textual data, for the language analysis of the reviews. After removing the reviews in languages other than Chinese and English, 133,419 English reviews and 62,285 Chinese reviews were obtained. For the subsequent analysis, we translated the Chinese reviews into

English using Google Translate.

Analytical Method

We used the fightin' words algorithm and conducted a sentiment analysis; these methods are commonly used in the NLP community. The fightin' words algorithm was used for feature selection and evaluation. In feature selection, the result is binary, i.e., inclusion or exclusion of the features (Monroe et al., 2009). For example, in this study, we want to know which words tourists from the two language groups use differently. Feature selection reduces the high dimensionality of the sample data. The objective of feature evaluation is to quantify the information on different features (Monroe et al., 2009). For example, we want to know how particular words are used differently by Chinese-speaking and English-speaking tourists to understand how tourists relate to the attributes. The objective is not to determine which terms are used by Chinese-speaking or English-speaking tourists but the frequency of use of these terms. Sentiment analysis is an active research area in the field of text mining and is also known as opinion mining (Fang & Zhan, 2015); in this approach, computational processing is used to extract the opinions, sentiments, and subjectivity of the authors of the text. Sentiment analysis can be conducted at three levels: document-level, sentence-level, and aspect-level. At the document-level, the entire document is considered one topic and is classified into positive or negative sentiment expressions; similarly, the other two levels focus on sentences or aspects. Sentiment analysis consists of three steps: sentiment identification, feature selection, and sentiment classification (Medhat, Hassan & Korashy, 2014). Classification techniques for sentiment analysis include machine learning methods, lexicon-based methods, and hybrid methods (Diana & Adam, 2011). An example of a machine learning method is the well-known ML algorithm and language function (Diana & Adam, 2011). Lexicon-based methods use a sentiment lexicon (a set of known and precompiled sentiment terms) and statistical or semantic methods to determine sentiment polarity; dictionary-based, corpus-based, and hybrid approaches have been used.

Sentiment analysis can be used to determine the sentiments of people regarding various topics. Traditional research has focused on the evaluation of accommodation experiences using satisfaction indicators. However, the use of only one indicator does not describe the sentiments of tourists adequately or the factors affecting the sentiment. In recent years, a trend has emerged to use sentiment analysis of online reviews. This method uses NLP and data mining algorithms to determine the opinions and attitudes of the authors of the text (Liu & Jian, 2018). Although traditional questionnaires have used evaluation indices and influencing factors of tourist satisfaction, this method is limited by the knowledge level of researchers and is prone to prejudice and wrong assumptions (Liu, Bao, & Chen, 2017). Compared with traditional market research methods (such as questionnaires and interviews), sentiment analysis is less costly and requires less time (Geetha et al., 2017), and hourly reviews can be obtained to determine the sentiment of tourists to avoid bias (Wiebe, 1994)

We used two steps in this study: identifying the attributes of Chinese-speaking and English-speaking tourists in the reviews and evaluating their perceptions of the attributes. Figure 1 shows a flowchart of the study; the steps are described in detail below.

[Figure 1 near here]

Step 1: Identification of the attributes that tourists emphasize

When using a large amount of text information, it is crucial to extract and summarize the key words or phrases to classify the text. In Step 1, we identified the differences between Chinese-speaking and English-speaking tourists in terms of the attributes they emphasized when describing the Airbnb experience, which was reflected in the word usage. For example, topics related to the kitchen were often observed in the English reviews but rarely appeared in the Chinese reviews; therefore, it can be concluded that English speakers are more focused on the kitchen in Airbnb accommodations than Chinese speakers. Text frequency analysis is often performed to determine differences in the emphasis. The most common text frequency analysis methods are the direct frequency comparison (Nakayama & Wan, 2018) and the term frequency-inverse document frequency (TF-IDF) comparison (Monroe, Colaresi, & Quinn, 2008). The direct frequency comparison method includes comparisons of the frequency difference (f1-f2) and frequency ratio (f1/f2). However, the frequency comparison method has some drawbacks; some phrases may be mentioned several times in Chinese reviews but not in English reviews, resulting in a higher weight of this phrase. Similarly, some phrases are very rare in Chinese or English reviews and are not suitable for distinguishing the two types of reviews. It is necessary to set a threshold for meaningful phrases in step 1. Moreover, it has to be considered that words with significance in the sample may not be significant overall; therefore, frequency regularization is required to determine the prior probability distribution. For these reasons, we used the fightin' words algorithm proposed by Monroe et al. (2009). The first step was to remove the stop words, which are words that frequently occur in documents but are meaningless (e.g., "the" and "an") (Choy, 2012). In sentiment analysis in NLP, these words are usually removed from the document to reduce the computational complexity or confusion. After removing unimportant sentences from the document, we vectorized the data. Subsequently, we used the fightin' words model, which automatically detected rare words, frequent words, and frequency gaps using Bayesian estimation and a Dirichlet prior. The score obtained in step 1 indicates the likelihood that a particular word is associated with a Chinese or English review. The more positive the score, the more likely it is that a particular word indicates the review of Chinese-speaking tourists, and the more negative the score, the more likely it is that the word indicates the review of English-speaking tourists. We identified the attributes associated with Airbnb from these words.

Step 2: Assessment of the perception of the attributes using sentiment analysis.

Two stages were involved in the sentiment analysis. The first stage was a document-level sentiment analysis; we treated each review as a document and conducted a sentiment analysis of the nearly 200,000 Chinese and English reviews. We used the NLP toolkit to determine the sentiment polarity and subjectivity of the reviews (Joachims, 1998). The model was trained with a large amount of data, and the neural network was used to obtain the sentiment polarity score, which ranges from -1 to 1. The higher the score is (>1), the more satisfied the tourist is, and vice versa. If the review is neutral, the sentiment polarity is zero. We also measured the subjectivity of the Chinese and English reviews to determine differences between the two groups. The subjectivity scores ranged from 0 to 1; the higher the score, the more subjective the reviews are. For example, “in my opinion” and “I think” indicate that the review is subjective. In step 2, we obtained the sentiment polarity and subjective scores and calculated the average, extrema, and variance of all Chinese and English reviews to conduct a comparative analysis.

The second stage was a fine-grained sentence-level and aspect-level sentiment analysis. We performed sentence tokenization, which splits the sentences into words and creates a bag of words. The following steps were performed: (i) Breaking the sentence into tokens; (ii) lowercasing the tokens; (iii) removing punctuations; (iv) removing stop words; (v) stemming the tokens. We used the classification and summary of the attributes obtained in step 1 to create a set of dictionaries related to Airbnb. The attribute dictionary is a set of keywords indicating that the sentence focuses on a particular attribute. In step

2, we conducted a fine-grained sentiment analysis of the attributes mentioned in the reviews to determine the perception of the tourists. In traditional sentiment analysis, researchers often use software to determine sentiments; this analysis is based on sentiment word analysis (lexicon-based approach) to identify the sentiment intensity of the words in the text. This approach has two limitations: first, when the text is short, there may be no few words indicating sentiment, resulting in inaccurate or unsuccessful identification. Second, when the text contains complex semantics, such as multiple negation and suggestions, misidentification of sentiment words may occur. Therefore, in step 2, we used a neural network-based approach (machine learning) for sentiment analysis. After using extensive pre-training of the annotated text, the neural network can identify complex sentiment expressions and the meaning in sentence patterns to obtain an accurate sentiment polarity score for the subsequent analysis. In reality, Airbnb online reviews commonly have two features: different sentences are often related to different aspects, and the degree of correlation between the sentences is relatively small. For example, in one review, it was stated that "…the location of this Airbnb is quite good. But because this is a multi-story building, the toilets are smelling bad". The two sentences in this review describe different aspects and have different sentiments; second, there are recurring keywords in the review, such as host, location, and other words mentioned by most of the reviewers. Specific keywords are used to describe the attributes and convey the meaning. Therefore, the neural network-based sentiment analysis model is implemented based on a commonly used (Dominik, 2017; Saha, Yadav & Ranjan, 2017; Sahni, Chandak, Chedeti & Singh, 2017) text analysis tool in the NLP community; this tool has a state-of-the-art sentiment analysis algorithm that detects sentiment based on expression and uses a pre-trained model.

Results

The attributes mentioned in the reviews and the emphasis difference

Step 1 used the fightin' words algorithm to identify the attributes of the Airbnb mentioned in the Chinese and English reviews and determine the differences in the emphasis. We categorized the attributes for the three aspects (host, accommodation, and location). Insights were obtained by identifying similarities and differences in the attributes between the Chinese-speaking and English-speaking tourists. For example, "price" appeared in our results, but it was not part of the three aspects (host, accommodation, and location); therefore, we created a fourth category for "price". After removing meaningless phrases and phrases that are used differently because of translation or synonyms, the final results were obtained (Figure 2); we observed significant differences in the attributes between Chinese-speaking and English-speaking tourists.

[Figure 2 near here]

"○" represents the attributes of the Chinese-speaking tourists in the reviews and "△" represents the attributes of the English-speaking tourists. The higher the position of "○", the greater the emphasis of the attributes is for Chinese-speaking tourists. The lower the position of "△", the higher the emphasis of the attributes is for English-speaking tourists. For instance, the most important attribute for Chinese-speaking tourists is "MTR", whereas, for English-speaking tourists, the most important attribute is a "clean place".

The sentiments of the attributes and the perception differences

The results of the sentiment polarity of the 200,000 review samples are shown in Table 1 (results of step 2); there are differences in the perception between Chinese-speaking and

English-speaking tourists. In general, Chinese-speaking tourists have a more positive perception of Airbnb than English-speaking tourists. The scores of the most positive reviews in Chinese and English are both 1. Regarding the most negative reviews, English reviews are 25% more negative than Chinese reviews, suggesting that English-speaking tourists are more forthright in providing negative reviews. The variance of the sentiment polarity for English reviews is 10% greater than that for Chinese reviews, indicating that English-speaking tourists express their sentiments using a greater variety of expressions when writing online reviews (Nakayama & Wan, 2018).

[Table 1 near here]

The most positive reviews:

Best location! It is very near a train station and close to a few restaurants and bars. The apartment was clean and warm with well equipped kitchen essentials. The AC does a wonderful job of cooling down the apt after a hot and humid day in HK. The host provided accurate check-in instructions, left a lovely welcome note for us in the apartment, and was very quick to respond to all messages and questions. He’s a really great host!

非常好的入住体验。首先地理位置超好，离地铁站很近，还是在上环西环一带，实在太喜欢这里了；一个接一个的斜坡，有生果铺，有街市……到处都弥漫着生活气息，房子在第三街靠尽头处，就算白天的时间也很安静。其次性价比很高，五一床位都只要 500 多就可以入住，淡季应该更便宜。最后房东热情、耐心、友好，给到的入住贴士也都很好用～周围有许多不错的餐厅，懒得出街也可以自己在家做些简单的～房间内有些基本的餐具，可以满足一切需求～

The most negative reviews:

The building is terrible. Unfortunately, you don't get the correct address until AFTER you pay!!! My friends and I had a terrible experience at this apartment. It was the worst place I ever stayed at. He kept saying "it was the worst way to spend money on accommodation" until he entered the house.

其实怎样讲呢？一行五大四小，订房之前已经咨询过房东，也没给什么建议，只是负责收钱。自己身边也有很多香港人做事从来都是热心负责任，但这次真是大失所望。浴室只有一处，被子，床褥都没真正消毒，每一个家人都感觉痒，以及生自己皮肤敏感。本来想想算了，自己都了解，现在有些香港人已经同以前不一样了，但非常生气的是，早上九点我们都没穿好整理好，下个房客竟然破门而入，一大堆人。本来房间与实际大小描述不符，偏小。当时都不知道怎么办，再加上宝贝又发烧呕吐，真是好恼火。我们已经很守时按房东规定 11 点退房！唯一就是楼下有很多好吃的餐厅。

We measured the subjectivity of the Chinese and English reviews. As shown in Table 2, on average, the reviews from English-speaking tourists are more subjective than those from Chinese-speaking tourists. In general, English speaking tourists express their opinions more subjectively when writing reviews.

[Table 2 near here]

In the second stage, we used Textblob to conduct sentence-level fine-grained sentiment analysis to measure the perception of the two groups based on neural network analysis of the attributes. We classified the attributes into four classes (host, accommodation, location, and price), creating a keyword dictionary of the attributes of Airbnb. The sentiment polarity of the four classes was assessed. We used Seaborn and

Pandas to create boxplots of the sentiment scores (Figures 3, 4, 5, 6, and 7). The horizontal line in the middle of the boxplot represents the mean of the sentiment score, which can be regarded as the perception of the attribute. The higher the horizontal position, the higher the perception of the attribute is, and vice versa. The size of the box represents the variance; a larger indicates a larger variance and more sensitive to this attribute.

The results of the sentiment analysis suggest that Chinese-speaking and English-speaking tourists had positive perceptions of the four aspects of the Airbnb experience (Figure 3). Chinese-speaking tourists had a more positive perception of the host and were more selective than English-speaking tourists in terms of the accommodation, location, and price of Airbnb; this effect was most pronounced for the price. In summary, both groups of tourists had a positive perception of the host.

[Figure 3 near here]

Fine-grained sentiment analysis of the host

The analysis of the host aspect was focused on the role of the hosts in facilitating the Airbnb experience. We conducted a fine-grained sentiment analysis on the terms "helpful", "response", "attitude", "friendliness", "communication" and "patient" (Figure 4). The result showed that English-speaking tourists scored uniformly lower than Chinese-speaking tourists, indicating that the former had a less positive attitude toward the host than the latter based on the six terms.

[Figure 4 near here]

Fine-grained sentiment analysis of the accommodation

The accommodation aspect included the general environment, the room, bathroom, and kitchen, as well as facilities for daily use. The results of the fine-grained sentiment analysis are shown in Figure 5, indicating that Chinese-speaking tourists and English-speaking tourists had similar perceptions of the general environment. English-speaking tourists scored higher on the perception of the facilities and kitchen, whereas Chinese-speaking tourists scored higher on the perception of the room and kitchen, demonstrating that they had a more positive perception regarding these aspects.

[Figure 5 near here]

The perception of the general environment, the room, bathroom, and kitchen, and the facilities was further refined to understand the difference between English-speaking and Chinese-speaking tourists. The results are shown in Table 3.

[Table 3 near here]

Fine-grained sentiment analysis of the location

The location reflects the convenience of the accommodation in terms of transportation, major tourist attractions, and points of interest (e.g., shops, cafes). The results of the fine-grained sentiment analysis are shown in Figure 6. Chinese-speaking tourists were more satisfied with the transportation conditions near the accommodation, but they were more selective than the English-speaking tourists regarding the location of the accommodation and surrounding areas.

[Figure 6 near here]

The results of the refinement of the perception of the locations (transportation, major tourist attractions, and points of interest,s) are shown in Table 4.

[Table 4 near here]

Fine-grained sentiment analysis of the price

For the perception of the price, we performed fine-grained sentiment analysis of the terms “reasonable”, “expensive”, “cheap”, and “value” (Figure 7). Chinese-speaking tourists were more selective about the general price of housing and were more concerned with a low or reasonable price than English-speaking tourists. In addition, both groups showed a neutral attitude towards expensive housing.

Conclusion and recommendations

In this study, we used a large sample size of Airbnb reviews by English-speaking and Chinese-speaking tourists; we identified the attributes in the text to determine the tourists’ perceptions of various Airbnb attributes. The findings suggest that tourists from different cultural backgrounds speaking different languages have different preferences and perceptions of Airbnb attributes. We classified the attributes obtained from the review into four aspects (host, accommodation, location, and price). The underlying assumption of the study is that the attributes most frequently mentioned in tourist reviews represent factors indicative of tourist satisfaction (Tussyadiah & Zach, 2016). It must be noted that these key factors may affect tourists in different ways. According to the expectation-confirmation theory, tourist satisfaction is achieved by comparing service performance with prior expectations (Thong, Hong, & Tam, 2006). Tourists from different cultural backgrounds speaking different languages can be expected to have unique expectations regarding accommodation (Dolnicar & Grun, 2007), resulting in different preferences for hotel attributes. Tse and Ho (2009) concluded in their cross-cultural study of the hospitality industry that hotel customers from different cultural backgrounds had unique preferences regarding the service attributes. In this study, Chinese-speaking tourists valued the friendliness of hosts, which may be because Chinese tourists live in a collectivist culture and expect more politeness and consideration than western tourists who live in an individualistic culture. Regarding accommodation, English-speaking tourists were more concerned with the size of the room than Chinese-speaking tourists.

In Hong Kong, which is known for its high rents, property prices, and population density, smaller rooms are common. Asian tourists (e.g., Chinese-speaking tourists) may be more familiar with small spaces and highly populated areas, which are part of their daily lives; therefore, they do not have high expectations for the size of the room. In summary, these are some of the reasons that influence the preferences of tourists regarding Airbnb attributes.

In step 2, we evaluated the perception of the attributes of tourists using sentiment analysis. The results showed that Chinese reviews were more positive and objective than those of English-speaking tourists, which is in line with the results of other studies (Ha & Jang, 2010; Laroche et al., 2018; Nakayama & Wan, 2018). English-speaking tourists had a more negative perception than Chinese-speaking tourists, which can be explained from a contextual perspective. According to the concept of context (Hall, 1969), cultures are divided into low-context cultures and high-context cultures. Cateora (1987) proposed the concept of cultural hierarchy based on the concept of context, pointing out that western countries have a low-context culture, and eastern countries have a high-context culture. In our case, the Western culture with English as its language belongs to the low-context culture (Manrai, Manrai, Lascu, & Friedeborn, 2019), which emphasizes individualism. The Eastern culture with Chinese as its language belongs to the high-context culture (Kim, Pan, & Park, 1998), which emphasizes collectivism and harmony (Koh, Hu, & Clemons, 2010). Therefore, most individuals from this cultural background do not like to communicate negative information; if they do, they will minimize the negative aspect of the information (Manrai et al., 2019), and tend to communicate based on implicit contextual cues. The subjectivity score was higher for the English reviews than the Chinese reviews. The reason may be that western culture represents individualism, with an emphasis on individual independence, freedom, and spreading word of mouth information based on their inner feelings and drive (Lai, Zhen & Zhang, 2019). Therefore, English-speaking tourists are more likely to express their sentiments and opinions than Chinese-speaking tourists.

Regarding the host, Chinese-speaking tourists were more positive, which can be explained from the perspective of the concept of “guanxi”, which is unique to China. Guanxi refers to establishing interpersonal relationships to ensure benefits (Luo, 1997) and is an important cultural value that dominates the behavior of Chinese people (Chan, 2006; Lee & Dawes, 2005). Because the Airbnb hosts may have connections with tourists before the check-in, guanxi is developed. Posting an unpleasant experience with a host one can have a significant negative impact on the image of an Airbnb host. Since Chinese tourists are aware of the impact of online reviews, tourists who have developed guanxi with the host may consider the interests of the person in this relationship before sharing reviews online. As a result, the presence of guanxi between tourists and hosts may increase or reduce the likelihood of posting positive or negative online reviews.

Regarding the other three aspects (location, accommodation, and price), Chinese travelers are more selective than English tourists. The reason is that the power distance index in China is significantly higher than that in many western countries (Hofstede, 2001). Previous studies have shown that consumers with a higher power distance index and from a collectivist culture are stricter regarding the functional attributes of products (Faqih & Jaradat, 2015; Krishnan & Subramanyam, 2004; Udo et al., 2012). In our case, the accommodation and location are functional attributes of Airbnb housing. Regarding the price, Guttentag (2015) believed that price is the main reason for using Airbnb. Considering the importance of frugality in a collectivist culture (Gong, 2003), Chinese tourists are more eager to get a good deal; therefore, they are more selective about the price than English-speaking tourists.

This study identified and measured the differences in the emphasis and perception of Airbnb attributes of tourists in the two language groups, providing a new perspective and direction for cultural differences research. This research contributes to the hospitality and consumer behavior literature, enriching the body of literature on Airbnb online reviews. The results confirm the results of and add knowledge to the dimensions proposed by Schuckert et al. (2015) and Francesco and Roberta (2019). We analyzed Airbnb reviews to contribute to the limited literature on this topic to provide new information for the rapidly growing hospitality industry. The findings of this study enrich the literature in two ways: (1) they provide an insight into the behavioral preferences of different consumers by identifying key attributes and the perceptions of tourists; (2) they clarify the results of cultural differences so that better marketing and management strategies can be developed. This study confirms the benefits of extracting market and competitive intelligence from high-volume, unstructured textual data to support marketing and management decisions in the travel and hospitality industry. We used different methods to summarize and explain the importance of information emerging from the massive amount of review data to obtain a better understanding of the consumer behavior of tourists from different cultures. The results highlight the growing importance of big data analysis for hotel management.

The method used in this study shows the potential of using traditional or modern NLP algorithms in the marketing field. In a recent study, Nakayama and Wan (2018) used commercial analysis software and basic frequency comparison in sentiment analysis. The methods used in this study have two advantages over traditional software analysis methods: first, we used the fightin' words lgorithm, which obtained more accurate and stable results than traditional frequency analysis due to the maximum likelihood estimation of the word frequency distribution. The fightin' words model has been widely used for data analysis in political science studies; our results demonstrate that this method provides excellent results in the field of marketing. Second, the use of code implementation and deep learning for the sentiment analysis model allowed us to analyze the sentiment of the text in detail with a custom approach. Compared with traditional analysis methods, the machine learning-based automatic sentiment analysis had two advantages: 1) lower resources were required, enabling the processing of larger amounts of data, and 2) there was less bias in the sentiment analysis regarding manual annotation and the development of the lexicon. The code implementation allowed us to customize the attributes and keywords related to Airbnb, create a keyword dictionary, and evaluate the attributes in the fine-grained sentiment analysis at the sentence level. In recent years, deep learning models have been extensively used for various NLP tasks; for the sentiment analysis, this method was able to provide more detailed and accurate sentiment expression. Due to these advantages, more profound text-based insights were obtained. Future researchers can use a similar method for sentiment analysis that requires assessing the emphasis of attributes in more complex situations.

Knowledge of the sentiment of tourists based on big data in the tourism field helps marketers to improve marketing strategies and methods for tourists with different cultural backgrounds, which has high application value. The findings of this study can help tourism and Airbnb operators determine the optimal allocation of scarce financial resources. Knowledge of the criteria of tourist perception helps to identify the important factors that are needed to categorize tourists based on their perceptions. Tourist perception can be improved it the Airbnb host is aware of the perceptions of tourists from different cultural backgrounds, thereby addressing problems related to tourist perception with the accommodation.

The findings can help hosts understand whether visitors from a particular cultural background are concerned with specific attributes of Airbnb. For example, our results suggest that Chinese-speaking tourists care about the proximity to a convenience store, whereas English-speaking tourists are more concerned about whether there is a coffee shop, bar, and night market nearby. According to different attributes, the Airbnb hosts can attract tourists by using advertisements. In addition, by being aware of the perception of different cultural groups, certain aspects of the accommodation can be improved in a targeted manner to improve tourist satisfaction. For example, English-speaking tourists are more concerned with the quality of service, whereas Chinese-speaking tourists are more interested in the price of the accommodation. Airbnb hosts need to focus on their response speed, attitude, friendliness, and patience in the communication process to ensure a high perception of the quality of service for English-speaking tourists. For Chinese-speaking tourists, marketers need to conduct market research to make the accommodation as cost-effective as possible. The results of this research suggest that Airbnb hosts should consider the different needs and expectations of individuals before designing specific marketing activities. The specific requirements and the characteristics of different cultures should be identified and understood because people from different cultural backgrounds focus on different aspects (Francesco & Roberta, 2019).

Limitations and future study directions

This study has three limitations. First, we only selected data from the Airbnb website in Hong Kong, which may generate bias since the data originated from a particular region of a single country. Therefore, in the future, studies on cultural differences should be extended to other international tourism destinations, such as Singapore, Paris, or New York.

The second limitation is the validity of the language classification. Although we proposed a new classification method to deal with large data sets and produced stable empirical results compared with traditional cultural studies, the validity of language classification requires further testing. Since the dataset contained nearly 200,000 reviews, we did not use a human translator, which would have been too time-consuming, but we used Google translation. No translation tool is perfect, and errors are inevitable. In this study, reviews written in English were categorized as one group, and those written in Chinese were into another group because English speakers may have common western cultural characteristics, even if they come from different countries (Schuckert et al., 2015). However, language classification requires additional studies because a foreigner's nationality and cultural background cannot be determined based solely on information obtained from the Airbnb website.

Finally, based on the research of Schuckert et al. (2015), in a future study, we plan to consider the differences in expectations. When considering cultural background differences, we assumed that there were differences in the demand and expectation. By considering the differences in expectation, we can provide additional critical information to help explain the differences in the emphasis and perception between the two groups.

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Study on the Sentimental Features of Chinese and English speaking Tourists' Satisfaction with the Airbnb

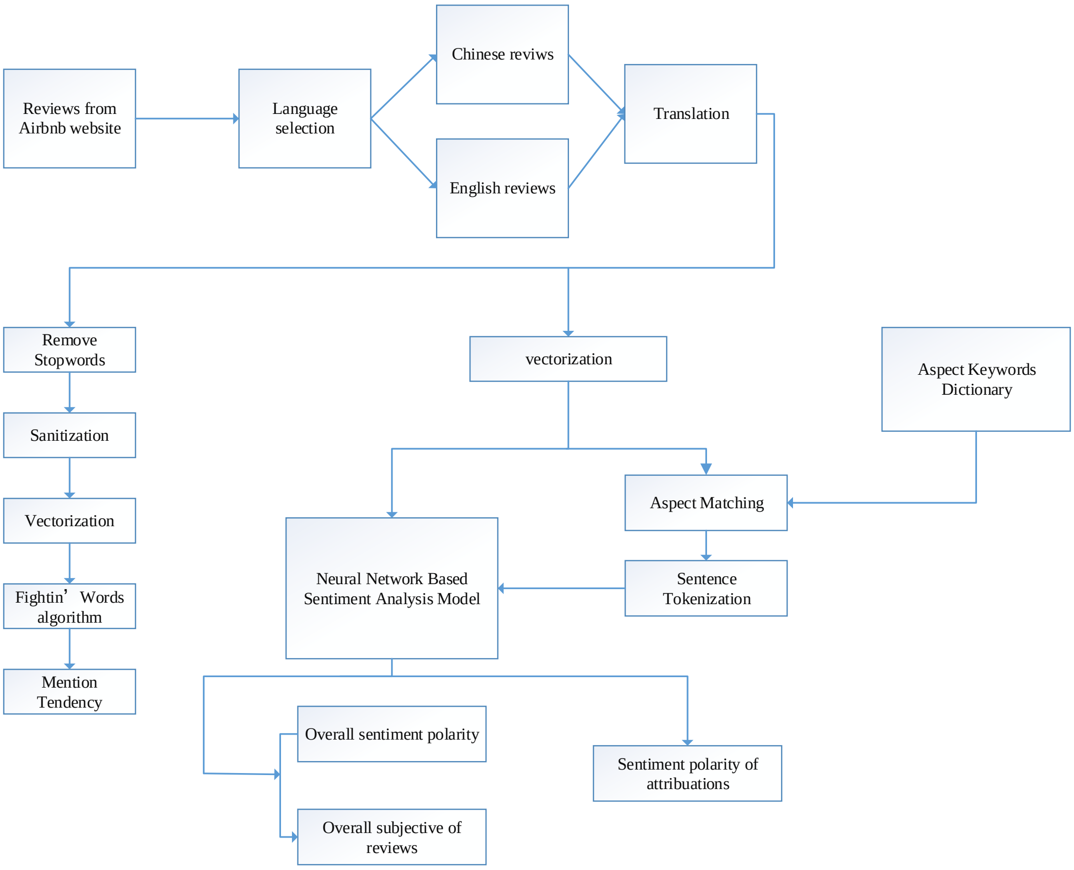

Figure 1. Analytical Steps

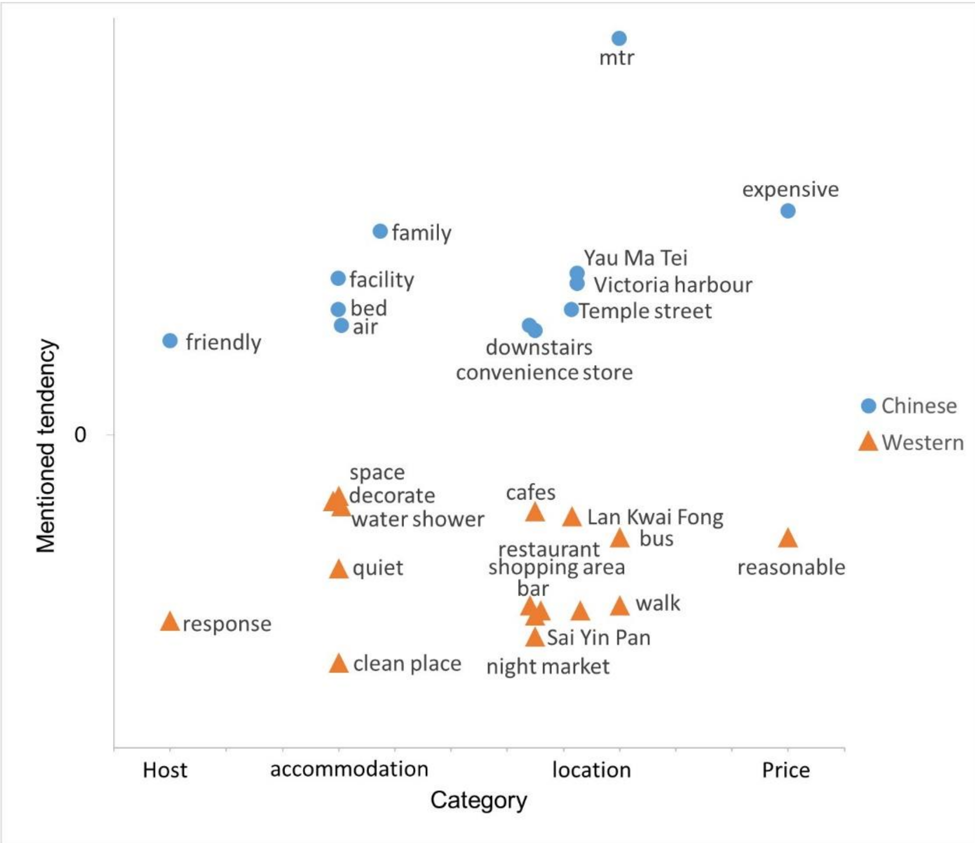

Figure 2. Differences of emphasis on attributions of Airbnb in Chinese and English reviews

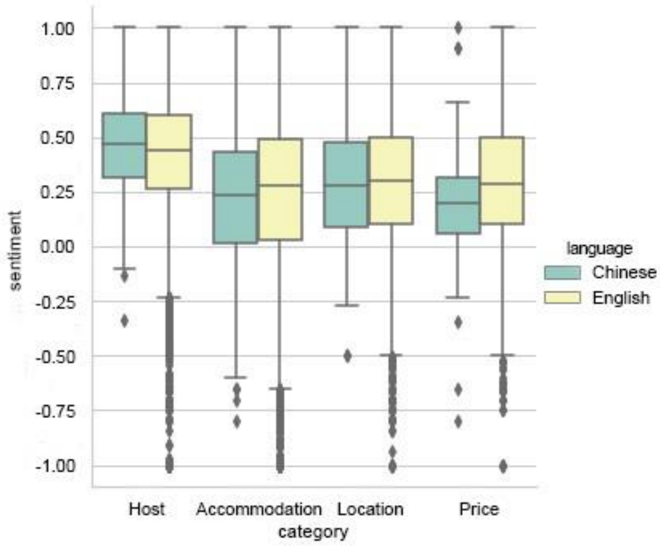

Figure 3. Differences of emphasis on attributes of Airbnb in Chinese and English reviews

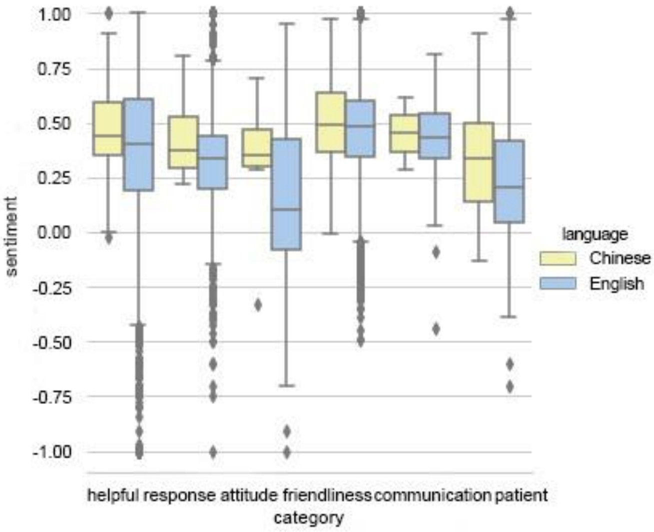

Figure 4. The sentiment scores of the host

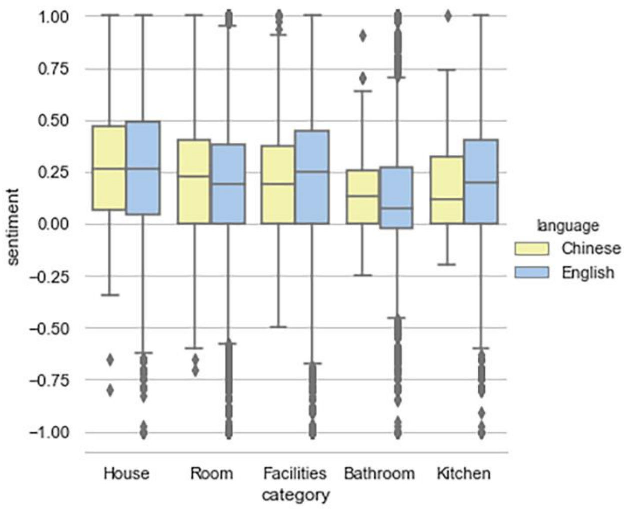

Figure 5. The sentiment scores of the accommodation

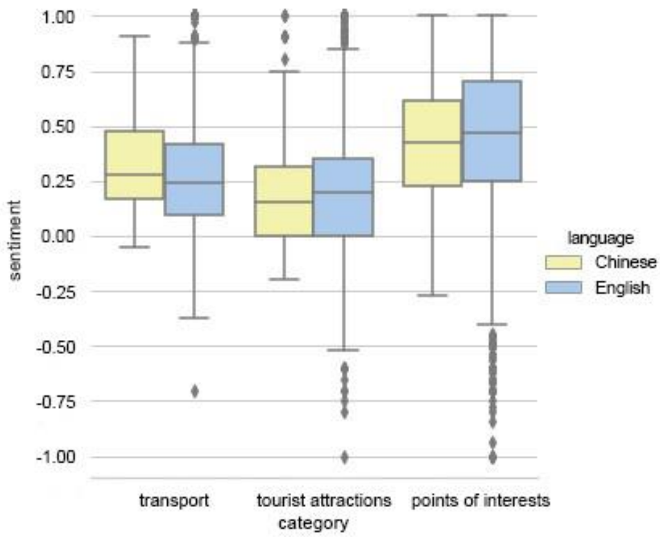

Figure 6. The sentiment scores of the location

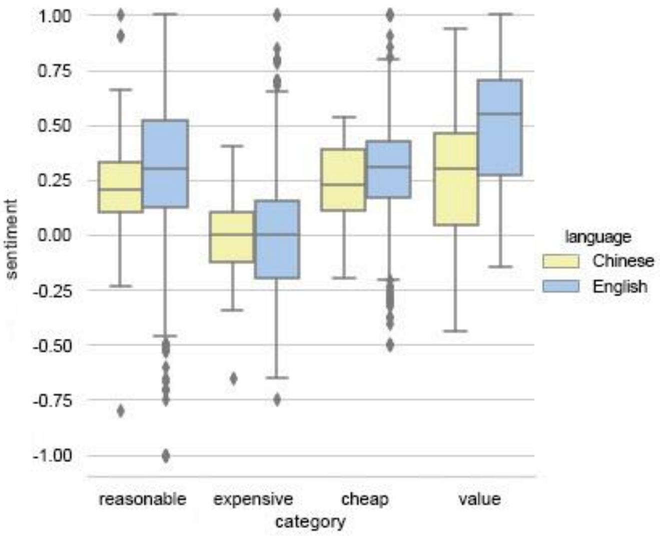

Figure 7. The sentiment scores of the price