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Exploring asymmetric effects of attribute performance on customer satisfaction in the hotel industry

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HIGHLIGHTS

- Whether the asymmetric effect of attribute performance (AP) on customer satisfaction (CS) varies across different types of hotels is examined.
- Whether the asymmetric effect of AP on CS varies across different types of travelers is examined.
- Whether the asymmetric effect of AP on CS varies across travelers from different regions is examined.
- The priorities of hotel attributes for different types of hotels with respect to different types of travelers and travelers from different regions are analyzed.

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ABSTRACT

Understanding the asymmetric effects of attribute performance (AP) on customer satisfaction (CS) is important for the managers in the hotel industry. Although several studies concerning this issue have been conducted, the varies of asymmetric effects across different market segments have not been revealed. To this end, this study aims to explore the asymmetric effects of AP on CS with respect to different market segments, including different types of hotels, different types of travelers and travelers from different regions. Four theories, i.e., expectation-disconfirmation paradigm, three-factor theory of CS, customer delight theory and prospect theory, are adopted to explain the formation of CS from the perspective of different market segments. The penalty–reward contrast analysis (PRCA) and asymmetric impact-performance analysis (AIPA) are used to analyze 1,547,869 user-generated ratings collected form *TripAdvisor* posted by the travelers from 140 countries concerning 9,596 hotels from 75 capital cities around the world. The results suggest that the asymmetric effects of AP on CS may vary across different market segments, including different types of hotels, different types of travelers and travelers from different regions. In addition, the priorities of hotel attributes for each type of hotel with respect to different types of travelers and travelers from different regions are also analyzed by AIPA. The obtained results will be valuable for researchers to conduct further studies and hotel managers to formulate improvement strategies.

1. Introduction

Customer satisfaction (CS) is the key to the success of every organization in the hospitality field, and has been extensively studied and discussed in recent years due to its increasing importance to managers (Chen, 2015; Slevitch & Oh, 2010; Tontini, dos Santos Bento, Milbratz, Volles, & Ferrari, 2017; Xiang, Schwartz, Gerdes, & Uysal, 2015). To better evaluate and investigate CS, most researchers recommend the multi-attribute approach, i.e., CS should be measured through the performances of multiple attributes (Chen, 2015; Mihalič, 2013; Slevitch & Oh, 2010). Based on the multi-attribute approach, most CS studies have conceptualized the relationship between attribute performance (AP) and CS as linear or symmetric (Chen, 2014, 2015; Liu et al., 2017; Slevitch & Oh, 2010). In these studies, an implicit assumption was that the same amount changes of attribute's positive and negative performances would lead to the same amount changes of CS. However, the symmetric assumption has been criticized and proved to be not always holding true. Some existing studies indicate that the relationship

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between AP and CS can be nonlinear or asymmetric. That is, the same amount changes of attribute's positive and negative performances would lead to different amount changes of CS (Albayrak, 2015; Albayrak & Caber, 2013a,b; Caber, Albayrak, & Loiacono, 2013; Matzler, Bailom, Hinterhuber, Renzl, & Pichler, 2004; Mikulić & Prebežac, 2008; Mittal, Ross Jr, & Baldasare (1998); Slevitch & Oh, 2010). Analyzing the asymmetric relationship between AP and CS, and identifying the category of each attribute are important for determining the priorities of hotel attributes and increasing CS effectively.

According to three-factor theory of CS, the attributes with different asymmetrical relationships can be classified into three categories, i.e., excitement attributes, basic attributes and performance attributes (Albayrak & Caber, 2015; Kano, Seraku, Takahashi, & Tsuji, 1984; Lai & Hitchcock, 2016; Matzler et al., 2004). Additionally, in accordance with the expectation-disconfirmation paradigm (Oliver, 1980), CS is the discrepancy between customer's expectations and the perceived performance (or quality). Considering the above two theories synthetically, basic attributes are taken for granted, which do not produce CS when the perceived performance exceed customer's expectations, but result in customer dissatisfaction if the perceived performance not exceed customers' expectations. In other words, poor performance of a basic attribute has a stronger influence on CS than its good performance. Performance attributes will result in dissatisfaction when customer's expectations are not exceeded and satisfaction when customer expectations are exceeded. In other words, the same amount changes of attribute's positive and negative performances would lead to the same amount changes of CS. Excitement attributes offer customer satisfaction when customer expectations are exceeded but do not give rise to dissatisfaction when customer expectations are not exceeded. In other words, good performance of an excitement attribute has a greater impact on CS than its poor performance. Therefore, the asymmetric relationship between AP and CS (or the categories of attributes) are mainly determined by customers' perceptions and expectations (or reference points) toward the attributes (Davras & Caber, 2019; Kano, 2001; Masiero, Pan, & Heo, 2016). It is necessary to point out that the customers' expectations vary with different market segments, such as different types of hotels (Xu & Li, 2016; Zhang, Ye, & Law, 2011), different types of travelers (Banerjee & Chua, 2016; Kashyap & Bojanic, 2000; Radojevic, Stanisic, Stanic, & Davidson, 2018; Yavas & Babakus, 2005) and travelers from different regions (Banerjee & Chua, 2016; Matzler, Strobl, Stokburger-Sauer, Bobovnicky, & Bauer, 2016; Matzler, Renzl, & Rothenberger, 2006; McKercher, Ho, & Du Cros, 2005; Poon & Low, 2005). Therefore, the asymmetric relationship between AP and CS should not be the same across different market segments (Füller & Matzler, 2008; Matzler & Renzl, 2007). However, the research on the asymmetric effects of AP and CS concerning different market segments is still rare, especially in the hotel industry.

According to the grade or star rating of hotels, the hotels can be divided into three types, i.e., economy hotel, midscale hotel and luxury hotel (Xu & Li, 2016; Zhang et al., 2011). Studies have shown that customers' perceptions, expectations and preferences vary across different types of hotels (Xu & Li, 2016; Zhang et al., 2011). However, whether the asymmetrical relationship between AP and CS varies across different types of hotels has not been verified. Thus, the first research question in this study is:

Q1: Whether the asymmetrical relationship between AP and CS varies across different types of hotels?

Besides, according to the travel motivations, majority of travelers can be classified into two categories, i.e., business traveler and leisure traveler (Radojevic et al., 2018). Studies have shown that business traveler and leisure traveler have different hotel evaluation criteria and expectations (Banerjee & Chua, 2016; Kashyap & Bojanic, 2000; Radojevic et al., 2018; Yavas & Babakus, 2005). However, whether the asymmetrical relationship between AP and CS varies across different types of travelers has not been verified. Thus, the second research question in this study is:

Q2: Whether the asymmetrical relationship between AP and CS varies across different types of travelers?

Meanwhile, travelers from different regions may have different cultural backgrounds (Wong, McKercher, & Li, 2016). The differences among travelers' regions and cultural backgrounds influence their preference and expectations for hotel attributes, such as location, cleanliness and value for money (Banerjee & Chua, 2016; Matzler et al., 2016; Matzler et al., 2006; McKercher et al., 2005; Poon & Low, 2005). Hotels favored by the travelers from a particular region may not be liked by the travelers from other region (Liu et al., 2017). In addition, according to the study of Liu et al. (2017), the symmetric relationship between AP and CS varies across travelers from different regions. However, whether the asymmetrical relationship between AP and CS varies across travelers from different regions has not been verified. Thus, the third research question in this study is:

Q3: Whether the asymmetrical relationship between AP and CS varies across travelers from different regions?

Moreover, asymmetric impact-performance analysis (AIPA) is regarded as an effective technique for understanding CS and formulating improvement strategies for products/services by determining the priority of product/service attributes considering both the asymmetric effects of the attributes on CS and their performances at the same time (Albayrak & Caber, 2015; Caber et al., 2013). However, there is no attempt to conduct AIPA considering different types of travelers and travelers from different regions. Thus, the fourth research question in this study is:

Q4: To improving the quality of hotel attributes, what are the priorities of hotel attributes for each type of hotel with respect to different types of travelers and travelers from different regions?

In the traditional environment, to answer the above four questions, the large-scale customer surveys should be conducted, which would be expensive in terms of time and money. With the rapid development of information technology, massive user-generated ratings of hotels have emerged on the Internet (Guo, Barnes, & Jia, 2017; Sotiriadis & Van Zyl, 2013). These user-generated ratings can be regarded as peer-generated evaluations which represent customers' personal experience (Radojevic et al., 2018; Zhang et al., 2011). Existing literatures have shown that these user-generated ratings can serve as data source for researchers to understand travelers' preferences and satisfaction (Guo et al., 2017; Liu et al., 2017; Ramanathan & Ramanathan, 2011; Zhang et al., 2011). In addition, massive user-generated ratings can be easily collected through the Internet, which can cover different types of hotels, different types of travelers and travelers from different regions. Therefore, user-generated ratings are used to investigate the above questions in this study. Following Radojevic, Stanisic, and Stanic (2017), Radojevic et al. (2018) and Liu et al. (2017), the user-generated ratings in *TripAdvisor* (https://www.tripadvisor.com/), one of the most leading tourism websites, are used in this study. In *TripAdvisor* website, overall customer satisfaction (OCS), and customer satisfaction on six relevant attributes ("Location", "Cleanliness", "Rooms", "Service", "Sleep quality" and "Value") can be obtained.

Based on the above theoretical reasoning process and the data provided by the *TripAdvisor* website, a research framework of this study is given, as shown in Fig. 1. The OCS in the *TripAdvisor* website is regarded as the sum of the customer satisfactions of six attributes, i.e., "Location", "Cleanliness", "Rooms", "Service", "Sleep quality" and "Value". The customer satisfactions of the six attributes are affected by the perceived performance, customer's expectations and the asymmetric relationship. Meanwhile, the asymmetric relationship between AP and CS is affected by different market segments since customer's expectations vary across different market segments. Based on the research framework, by analyzing 1,547,869 user-generated ratings posted on *TripAdvisor* concerning six hotel attributes from travelers in 140 countries, we aim to explore the asymmetric effects of AP on CS with hotels by discriminating different types of hotels, different types of travelers and travelers from different regions.

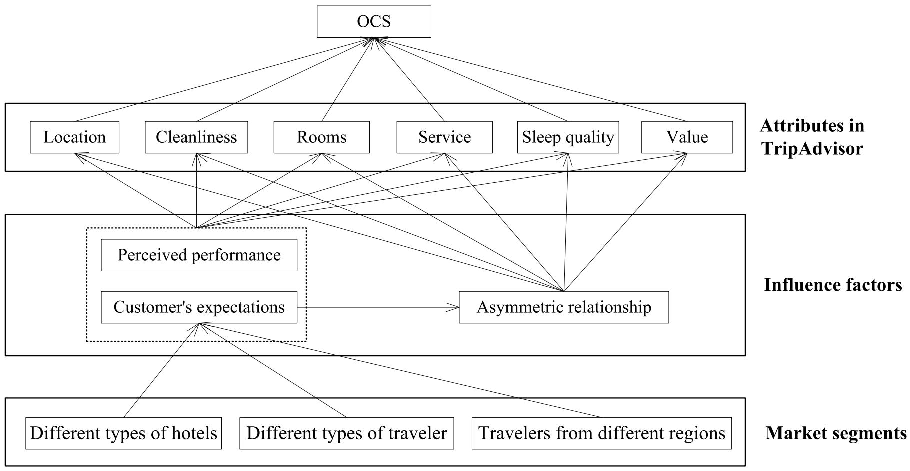

Fig. 1. The research framework of this study.

The remainder of this paper is organized as follows. Section 2 briefly reviews the relevant literatures. Section 3 presents the methodology. In Section 4, some results and discussions are given. Finally, Section 5 discusses the implications and limitations of this paper.

2. Related work

In this section, the related theoretical underpinnings of asymmetric effects of AP on CS are first given in Section 2.1. Then, studies on the asymmetric relationship between AP and CS in hotel industry are described in Section 2.2. Finally, studies on the use of user-generated data in tourist research are illustrated in Section 2.3.

2.1. The related theoretical underpinnings of asymmetric effects of AP on CS

The related theoretical underpinnings of asymmetric effects of AP on CS mainly includes three aspects, i.e., (1) Symmetric versus asymmetric effects of AP on CS, (2) The theoretical underpinning of static asymmetries, and (3) Theoretical underpinnings of dynamic asymmetries, which will be respectively introduced in Section 2.1.1, Section 2.1.2 and Section 2.1.3.

2.1.1. Symmetric versus asymmetric effects of AP on CS

Traditionally, research on CS is based on the expectancy-disconfirmation paradigm (Oliver, Rust, & Varki, 1997), where CS is determined by the comparison between the perceived quality (i.e., AP) and expectations (a reference point). If an AP meets or exceeds a customer's expectations, then the customer will be satisfied with the attribute. On the contrary, if an AP is lower than a customer's expectations, then the customer will be unsatisfied with the attributes. A shortcoming of the expectancy-disconfirmation paradigm is that it assumes the same amount changes of attribute's positive and negative performances would lead to the same amount changes of CS. As a consequence, the relationship between AP and CS is expected to be linear or symmetric.

The symmetric assumption has been criticized and proved to be not always holding true. Some existing studies indicate that the relationship between AP and CS can be nonlinear or asymmetric (Albayrak & Caber, 2013a,b; Caber et al., 2013; Mittal, Ross Jr, & Baldasare, 1998; Mikulić & Prebežac, 2008; Slevitch & Oh, 2010). Starting with Kano et al. (1984), many researchers assume an asymmetric relationship between AP and CS, and classify the attributes into three categories, i.e., excitement (positive asymmetry) attributes, performance (symmetric) attributes and basic (negative asymmetry) attributes, based on their different asymmetric effects on CS, as shown in Fig. 2. The definitions of the three

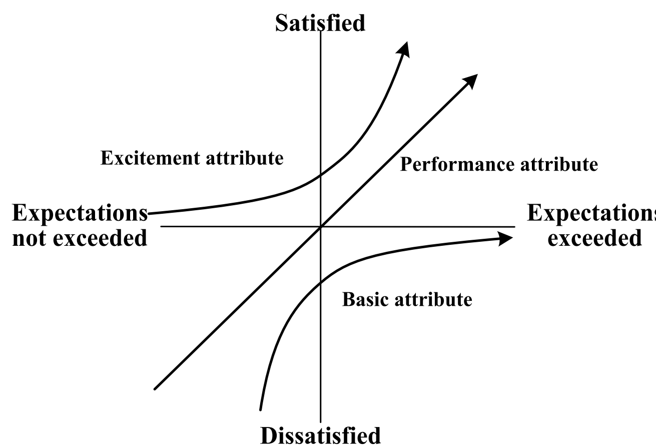

Fig. 2. Classification of attributes in the three-factor theory.

categories of attributes are illustrated as follows.

(1) Excitement attribute: This category of attribute offers customer satisfaction when customer expectations are exceeded but does not give rise to dissatisfaction when customer expectations are not exceeded. In other words, good performance of the attribute has a greater impact on customer satisfaction than its poor performance.
(2) Performance attribute: It is a category of attribute that customer expectations are positively related to customer satisfaction. In other words, the attribute will result in dissatisfaction when customer expectations are not exceeded and satisfaction when customer expectations are exceeded.
(3) Basic attribute: This category of attribute is the opposites of the excitement attribute and is taken for granted. That is, when customer expectations are exceeded, customers are just neutral, but customers will be very dissatisfied when customer expectations are not exceeded. In other words, poor performance of the attribute has a stronger influence on customer satisfaction than its good performance.

2.1.2. The theoretical underpinning of static asymmetries

As mentioned above, the asymmetric effects of AP on CS mainly consist of two categories, i.e., positive asymmetry (corresponding to excitement attributes) and negative asymmetry (corresponding to basic attributes). On the one hand, the theoretical logic for the existence of positive asymmetries lies in customer delight theory (Falk, Hammerschmidt, & Schepers, 2010; Oliver et al., 1997). Customer delight is “a profoundly positive emotional state generally resulting from having one's expectations exceeded to a surprising degree” (Rust & Oliver, 2000). If there are no generally accepted standard of performance, then these attributes are delight-creating (Falk et al., 2010). They offer customer satisfaction when customer expectations are exceeded but do not give rise to any dissatisfaction when customer expectations are not exceeded.

On the other hand, negative asymmetries find their roots in prospect theory which suggest peoples' judgments display reference dependence and loss aversion (Kahneman & Tversky, 1979). Reference dependence indicates that individuals evaluate an outcome on its deviation from a reference point, not on its absolute level (Kőszegi & Rabin, 2006). Individuals evaluate outcomes as gains or losses result from a comparison to the reference point, where outcomes below and above the reference point are respectively regarded as losses and gains. Loss aversion indicates that individuals respond more strongly to loss than to gain. Corresponding to the asymmetric effects of AP on CS, a one-unit decrease in AP has a larger impact on CS than an equal amount of AP increase in the same attribute (Falk et al., 2010).

The above studies explain the asymmetric relationship between AP and CS from a static point of view. However, the asymmetric relationship between AP and CS is dynamic (Falk et al., 2010; Kano, 2001; Nilsson-Witell & Fundin, 2005). To better understand and illustrate dynamics, following Falk et al. (2010), the theoretical underpinnings of dynamic asymmetries will be introduced in Section 2.1.3.

2.1.3. Theoretical underpinnings of dynamic asymmetries

Reference points for customer satisfaction assessment are primarily determined through the prior usage of the service (Parasuraman, Berry, & Zeithaml, 1991). Thus, customers' expectations (or reference points) will be influenced by customers' experience, and as a consequence, they are likely to change over time (Mittal, Katrichis, & Kumar, 2001; Parasuraman, Zeithaml, & Malhotra, 2005). Normally, with the increase of customer's knowledge on services, the element of surprise fades. Consequently, the attributes that formerly considered as interesting and fresh gradually lose the ability to trigger customer delight. In addition, since expectations track performance evaluations, customers' expectations will increase with the increase of customers' knowledge (Rust & Oliver, 2000). An attribute will no longer show unlimited upside as the customer's cognition develops to the minimum standard concerning the attribute's performance. As a result, once the performance level of an attribute is lower than customer expectations, the negative effects on CS will emerge. Thus, the initial positive asymmetric effects gradually convert into symmetric effects, corresponding to Kano model, that is, an attribute changes from being an excitement item to a performance item. After this institutionalization, with the development of technology, the spread of word-of-mouth and the emergence of vicarious experience, an attribute would become a market standard (File, Cermak, & Prince, 1994). Therefore, after the delight element has faded, the symmetric effects will further develop into negative asymmetric effects, corresponding to Kano model, that is, an attribute will change from being a performance item to a basic item.

The above studies explain that the asymmetric relationship between AP and CS is dynamic (Falk et al., 2010; Kano, 2001; Nilsson-Witell & Fundin, 2005). Following Nilsson-Witell and Fundin (2005), the dynamic can be understood and interpreted in two ways, i.e., (1) individual perception toward an attribute changes over time and (2) different market segments perceive an attribute differently. Previous studies mainly focus on the dynamics of the asymmetric effects of AP on CS in a specific market over time (Falk et al., 2010; Kano, 2001). However, the research on the dynamics of the asymmetric effects of AP on CS concerning different market segments is still rare, especially in the hotel industry. Therefore, a special study on exploring asymmetric effects of AP on CS related to different market segments in the hotel industry is necessary.

2.2. Studies on the asymmetric relationship between AP and CS in hotel industry

Although asymmetric effects between AP and CS have been verified in different fields, the studies on asymmetric effects between AP and CS in the hotel industry are still very limited. Only several related studies can be found (Albayrak & Caber, 2015; Lai & Hitchcock, 2016; Lu & Stepchenkova, 2012; Matzler et al., 2006; Ramanathan & Ramanathan, 2011; Slevitch & Oh, 2010; Tontini et al., 2017; Xu & Li, 2016; Zhang & Cole, 2016; Zhou, Ye, Pearce, & Wu, 2014). According to the theory and method, these studies can be mainly classified into two categories, i.e., (1) studies on asymmetric effects between AP and CS based on penalty–reward contrast analysis (PRCA) and (2) studies on asymmetric effects between AP and CS based on critical incident technique (CIT). On the one hand, the main idea of the former is to classify attributes through the coefficients of a multiple regression equation. In the multiple regression equation, the performances (or ratings) of each attribute are re-corded as two dummy variables, where one dummy variable is formed by the high performance of the attribute and the other dummy variable is formed by the low performance of the attribute. By comparing the coefficients of the two dummy variables, the category of the attribute can be determined. For example, Matzler et al. (2006) measured the relative importance of hotel attributes in the formation of price and service satisfaction. In the study, based on 1,555 questionnaires collected from guests of 25 hotels, the asymmetric effects of the performances of five attributes (i.e., “Room”, “Friendliness & Service”, “Reception”, “Wellness area”, “Breakfast & Restaurant”) on CS were analyzed by the PRCA. The results show that “Room”, “Friendliness & Service” and “Reception” are basic attributes; “Restaurant & Breakfast” is an excitement attribute; “Wellness area” is a performance attribute. Albayrak and Caber (2015) compared two techniques (i.e., importance-performance analysis and asymmetric impact-performance analysis) for determining the priority of the hotel attributes based on attributes' influence on CS. In the study, based on 2,404 questionnaires of a five star hotel collected from Russian travelers, the asymmetric effects of the performances of nine attributes (i.e., “Food & beverage quality”, “Decoration of the rooms”, “Technical status of the hotel and rooms”, “Personnel”, “Animation activities”, “Overall cleanliness”, “Facilities for children”, “Beach” and “Swimming pool”) on CS were analyzed by the PRCA. The results show that “Beach”, “Technical status of the hotel” and “Rooms” are performance attributes; whereas the rest attributes are basic attributes. On the other hand, the main idea of the later is to classify attributes through incidents (occurrences, issues, events or processes) that significantly deviate from customers' expectations through asking customers to explain the negative and positive incident they can remember (Ee Kim & Lehto, 2012; Tontini et al., 2017). For example, Cadotte & Turgeon (1988) surveyed the typology of hotel attributes using the data from 260 hotel executives concerning the attributes that consumers compliment or complain about. The results show that “Location”, “Staff attitudes” and “Management knowledge” are excitement attributes (or satisfiers); “Check-in/check-out service”, “Parking availability”, “Price/value”, “Accuracy of bill” and “Availability of accommodation” are basic attributes (or dissatisfiers); “Quietness of surroundings” and “Cleanliness/neatness” are performance attributes (or critical attributes). Xu and Li (2016) surveyed the determinants of customer satisfaction and dissatisfaction toward four types of hotels (limited-service hotels, full-service hotels, suite hotels without food and beverage, and suite hotels with food and beverage). In the study, 3,480 customer reviews with both the positive and negative opinions from 580 hotels in U.S. were collected, and the determinants of customer satisfaction and dissatisfaction toward four types of hotels were analyzed using latent semantic analysis. The results show that the determinants of customer satisfaction and dissatisfaction vary across the four types of hotels.

It should be noted that in the hotel industry, the asymmetric effects of AP on CS is mainly carried out from a static point of view for a specific market. There is a clear lack of research on the asymmetric effects of AP on CS from a dynamics point of view related to different market segments, such as, different types of hotels, different types of travelers and travelers from different regions. Therefore, a special study on exploring asymmetric effects of AP on CS related to different market segments in the hotel industry is necessary.

2.3. Studies on the use of user-generated data in tourist research

User-generated data are "considered more objective, immense, and without sample bias, because reviews are posted spontaneously without laboratory effects unlike traditional questionnaires" (Schuckert, Liu, & Law, 2015). In addition, user-generated data are not only publicly available, easily collected and low cost, but also simpler for firms to monitor and manage (Guo et al., 2017). Therefore, more and more tourism researchers use user-generated data to carry out related research work in recent years (Hargreaves, 2015; Liu et al., 2017; Radojevic et al., 2018; Radojevic, Stanisic, & Stanic, 2015, 2017; Ramanathan & Ramanathan, 2011; Schuckert et al., 2015; Xu & Li, 2016; Ye, Law, & Gu, 2009; Zhang, Ye, Law, & Li, 2010; Zhang et al., 2011). According to the type of user-generated data, these studies can be classified into two categories, i.e., (1) studies based on user-generated reviews (text data) and (2) studies based on user-generated ratings (numerical data). The former mainly uses text mining methods to extract useful information from user-generated reviews, and then conducts further research based on the extracted information (Berezina, Bilgihan, Cobanoglu, & Okumus, 2016; Gao, Tang, Wang, & Yin, 2018; Guo et al., 2017; Phillips, Barnes, Zigan, & Schegg, 2017; Xiang et al., 2015; Xu & Li, 2016). For example, Guo et al. (2017) identified the key dimensions of customer service from 266,544 online reviews using latent dirichlet analysis. Xu and Li (2016) found that the determinants of customer satisfaction or dissatisfaction toward different types of hotels are different through 3,480 hotels reviews using latent semantic analysis. Xiang et al. (2015) deconstructed hotel guest experience and examined the association between guest experience and satisfaction ratings through 60,648 hotel reviews using a text analytical approach. The later mainly conducts related research directly through the customer overall satisfaction (overall rating) and customer ratings concerning specific attributes (e.g., ratings on rooms and service). For example, Zhang et al. (2011) examined whether and how hotel class and attributes ("Quality", "Room", "Cleanliness", "Location", and "Service") influence hotel room rates through the online ratings of 243 hotels using regression analysis. Liu et al. (2017) verified the determinants of customer satisfaction in hotel industry vary across customers with different languages through 412,784 online ratings. Radojevic et al. (2017) analyzed the factors influencing hotel customer satisfaction through 3,488,473 user-generated ratings using a multilevel analysis. Radojevic et al. (2018) examined the association between traveling for business and hotel customer satisfaction through 1,658,174 online ratings.

Existing literatures have shown that user-generated ratings can serve as a data source for researchers to understand travelers' preferences and satisfaction (Guo et al., 2017; Liu et al., 2017; Ramanathan & Ramanathan, 2011; Zhang et al., 2011). In addition, massive user-generated ratings can be easily collected through the Internet, which can cover different types of hotels, different types of travelers and travelers from different regions. Therefore, user-generated ratings are a promising source of data for exploring the asymmetric effects of AP on CS with hotels by discriminating different types of hotels, different types of travelers and travelers from different regions.

3. Methodology

3.1. Data collection

We collected the user-generated data from the *TripAdvisor* (https://www.tripadvisor.com/), which is the world's leading tourist website. In this study, we crawled the user-generated data of 9,596 hotels from 75 capital cities around the world, including a total of 3,214,673 user-generated data from travelers in 140 countries. Each user-generated data contains the information of the hotel star, traveler's nationality, travel type (solo, friends, family, business and couple), overall customer satisfaction (OCS), and customer satisfaction on six relevant attributes ("Location", "Cleanliness", "Rooms", "Service", "Sleep quality" and "Value"). OCS and customer satisfaction on six relevant attributes are rated using a 5-point Likert scale, where 1, 2, 3, 4 and 5 are respectively indicate "terrible, "poor", "average", "very good" and "excellent". Since the customer satisfaction on six specific attributes are not mandatory, there are missing data about these six attributes. After deleting the missing data, we finally obtained 1,547,869 valid data.

Following the study of Zhang et al. (2011), according to the hotel star, the hotels were categorized into three types, i.e., economy hotel (1-, 1.5-, 2- and 2.5-stars hotels), midscale hotel (3- and 3.5-stars hotel) and luxury hotel (4-, 4.5- and 5-stars hotels). The numbers of the collected data with respect to economy hotel, midscale hotel and luxury hotel are 105,245, 494,825 and 947,799, respectively. The details are given in Table 1. It can be seen from Table 1, with the improvement of the hotel level, the average values of both OCS and customer satisfaction on six relevant attributes increase gradually, indicating that the hotel service level is improved with the improvement of the hotel level; and with the improvement of the hotel level, the variance values of both OCS and customer satisfaction on six relevant attributes decrease gradually, indicating that the consistency of customer satisfaction with hotel services increases with the improvement of hotel level.

3.2. Research method

3.2.1. Penalty–reward contrast analysis

The penalty–reward contrast analysis (PRCA) proposed by Brandt (1987), is a commonly used method for exploring the asymmetric effect of AP on CS and categorizing attributes into different categories (Albayrak & Caber, 2015; Matzler et al., 2006). Therefore, the PRCA is adopted in this study. A brief description of the PRCA is given below.

For each attribute, two dummy variables are created by re-coded attribute satisfaction ratings, denoted as d^i_{lp} and d^i_{hp}. The first dummy variable (d^i_{lp}) is created by recoding the lowest attribute satisfaction ratings (i.e., 1) as "1", meanwhile all other ratings (i.e., 2, 3, 4 and 5) are recoded as "0". The first dummy variable (d^i_{lp}) is adopted to estimate the impact of attributes' extremely low performance on CS (Mikulić & Prebežac, 2008). The second dummy variable (d^i_{hp}) is created by recoding the highest attribute satisfaction ratings (i.e., 5) as "1", meanwhile all other ratings (i.e., 1, 2, 3 and 4) are recoded as "0". The second dummy variable (d^i_{lp}) is adopted to estimate the impact of attributes' extremely high performance on CS (Mikulić & Prebežac, 2008). Based on the obtained two dummy variables, a multiple regression analysis is conducted to estimate the impact of each attribute on CS at extremely low and extremely high performance levels, i.e.,

$$\text{OCS} = \beta_0 + \sum_{i=1}^{n} \left(\beta^i_{\text{lp}} d^i_{\text{lp}} + \beta^i_{\text{hp}} d^i_{\text{hp}} \right) + \varepsilon \tag{1}$$

where β^i_{lp} and β^i_{hp} respectively denote the incremental change of OCS at extremely low performance level (penalty coefficient) and high performance level (reward coefficient) of each attribute; $n = 6$, i.e., the six attributes. It should be noted that there are currently two ways to obtain the penalty coefficient and reward coefficient, i.e., using the standardized regression coefficients (Albayrak & Caber, 2013b; Caber et al., 2013) and using the unstandardized regression coefficients (Alegre & Garau, 2011; Mikulić & Prebežac, 2011a,b; Mikulić & Prebežac, 2012). Through theoretical analysis and empirical research, Mikulić and

Table 1
The final data concerning the hotel type.

Hotel type	Statistics	OCS	Location	Cleanliness	Rooms	Service	Sleep quality	Value
Economy hotel	Mean	3.60	4.24	3.81	3.39	3.74	3.62	3.80
	Variance	1.414	0.866	1.470	1.433	1.491	1.514	1.514
Midscale hotel	Mean	3.88	4.31	4.11	3.75	3.98	3.93	3.94
	Variance	1.081	0.785	1.029	1.143	1.171	1.189	1.160
Luxury hotel	Mean	4.22	4.42	4.44	4.17	4.27	4.29	4.03
	Variance	0.866	0.673	0.694	0.909	0.954	0.883	0.989

Prebežac (2012) shows that using unstandardized regression coefficients is more reasonable than using the standardized regression coefficients to explore asymmetric effects in customer satisfaction. Therefore, following Mikulić and Prebežac (2012), the unstandardized regression coefficients are used to obtain the penalty coefficient and reward coefficient in this study.

According to the regression coefficients and their significance obtained by Eq. (1), attributes can be classified into different categories (basic, performance and excitement) through three categories of classification techniques, i.e., (1) by comparing the significance of the coefficients, (2) by using the discrepancy test, and (3) by using the index value (Albayrak & Caber, 2013a). The first category of the classification technique is to classify attributes by comparing the significance of the regression coefficients. Specifically, if the penalty coefficient is in insignificant and the reward coefficient is significant, then the attribute in question is classified as an excitement attribute. If both the penalty and reward coefficients are significant, then the attribute is a performance attribute. If the penalty coefficient is significant and the reward coefficient is insignificant, then the attribute is classified as a basic attribute (Fuchs & Weiermair, 2004; Lin, Yang, Chan, & Sheu, 2010). On the basis of the first category of research, the Wald test is adopted, in the second category of classification technique, to test the equality of penalty and reward coefficients for an attribute that both its penalty and reward coefficients are significant. Specifically, if the absolute value of the penalty coefficient is significantly higher than that of the reward coefficient, the attribute is classified as a basic attribute. If their differences are statistically not significant, then the attribute is a performance attribute. If the absolute value of the penalty coefficient is significantly lower than that of the reward coefficient, the attribute is classified as an excitement attribute (Alegre & Garau, 2011). It should be noted that although these two categories of classification techniques have been used in some studies and proved to be effective to some extent, they cannot be used in cases where both the penalty and reward coefficients are not significant (Alegre & Garau, 2011; Matzler & Sauerwein, 2002). Unlike the first two categories of classification techniques, the third category of classification technique mainly determines the category of attributes by calculating index values based on the obtained penalty and reward coefficients (Füller & Matzler, 2008; Matzler & Renzl, 2007; Mikulić & Prebežac, 2008). At present, there are two methods for calculating the index value, i.e., "impact ratio" (IR) and "impact asymmetry" (IA). The IR is calculated by dividing reward coefficient by the penalty coefficient. Consequently, the IR theoretically changes between negative infinite and positive infinite, which complicates comparisons of calculated indices (Mikulić & Prebežac, 2008). On the contrary, the index value of IA ranges from -1 to $+1$, which simplifies comparisons of calculated indices. Additionally, the asymmetric impact-performance analysis (AIPA) is employed in this study to determine the priorities of hotel attributes, which involves two metrics, i.e., IA index and attribute performance. Therefore, the IA index is adopted in this study to classify attributes into different categories. The details are given as follows.

In accordance with the obtained β_{lp}^{i} and β_{hp}^{i}, the IA index can be calculated by Eq. (2) (Albayrak & Caber, 2015; Mikulić & Prebežac, 2008).

$$IA_i = \frac{\left|\beta_{\mathrm{hp}}^{i}\right| - \left|\beta_{\mathrm{lp}}^{i}\right|}{\left|\beta_{\mathrm{lp}}^{i}\right| + \left|\beta_{\mathrm{hp}}^{i}\right|} \tag{2}$$

Obviously, $-1 \le \mathrm{IA}_i \le 1$. The meaning of the IA_i interpreted as follows:

(i) If $\mathrm{IA}_i = -1$ (i.e., $\beta_{\mathrm{hp}}^{i} = 0$), then it means that the attribute has only dissatisfaction-generating potential and without any satisfaction-generating potential.
(ii) If $\mathrm{IA}_i = 0$ (i.e., $\beta_{\mathrm{hp}}^{i} = \beta_{\mathrm{lp}}^{i}$), then it means that the attribute has equal dissatisfaction- and satisfaction-generating potentials.
(iii) If $\mathrm{IA}_i = 1$ (i.e., $\beta_{\mathrm{lp}}^{i} = 0$), then it means that the attribute has only satisfaction-generating potential and without any dissatisfaction-generating potential.

To classify the attributes into different categories, a cut-off point θ is defined subjectively, $0 < \theta < 1$. Following the studies of Albayrak and Caber (2015) and Mikulić and Prebežac (2008), here we define $\theta = 0.1$. Then, the category of each attribute can be determined. Specifically, if $-1 \le \mathrm{IA}_i < -0.1$, then the attribute is regarded as a basic attribute; if $-0.1 \le \mathrm{IA}_i \le 0.1$, then the attribute is regarded as a performance attribute; if $0.1 < \mathrm{IA}_i \le 1$, then the attribute is regarded as an excitement attribute.

3.2.2. Asymmetric impact-performance analysis

Asymmetric impact-performance analysis (AIPA) is a method for understanding CS and formulating improvement strategies for products/services (Albayrak & Caber, 2015; Caber et al., 2013). Based on the AIPA, researchers and managers can simultaneously consider both attributes' performances and their asymmetrical effect on CS for formulating improvement strategies for products/services (Albayrak & Caber, 2015). Fig. 3 is an example of the AIPA plot. The horizontal axis of the AIPA plot is the performance of the attribute, and the vertical axis is the IA index. The two blue horizontal lines are the cut-off lines (0.1 and -0.1) for classifying attributes into three categories, i.e., basic attributes, performance attributes and excitement attributes. The blue vertical line is the cut-off line for classifying attributes into two categories, i.e., high performance and low performance. The position of the vertical cut-off line is determined by calculating the average value of the performance of all attributes. Therefore, attributes are classified into six categories, i.e., high-performance excitement (HE) attributes, high-performance performance (HP) attributes, high-performance basic attributes (HB), low-performance basic (LB) attributes, low-performance performance (LP) attributes and low-performance excitement (LE) attributes, indicated as A_1 to A_6 in Fig. 3. According to the three-factor theory (Kano et al., 1984), basic attributes have great potential to generate dissatisfaction if their performances are low, but little potential to generate satisfaction if their performances are high; performance attributes have equal potential to generate dissatisfaction and satisfaction if their performance are low and high; excitement attributes have great potential to generate satisfaction if their performances are high, but little potential to generate dissatisfaction if their performances are low. Therefore, to maximize the improvement of CS

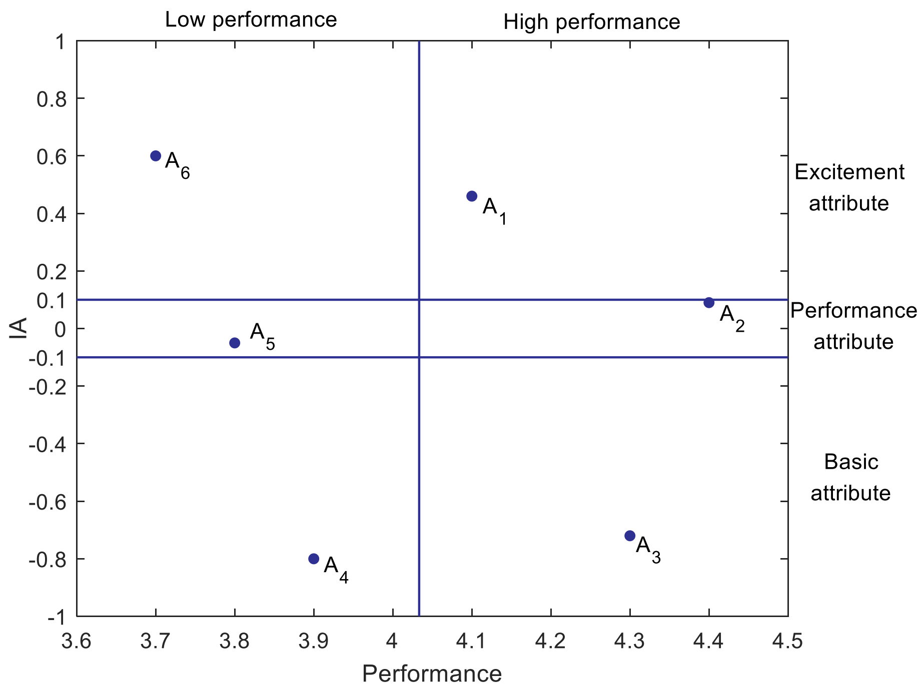

Fig. 3. An example of the AIPA plot.

with minimal investment in resources, on the one hand, managers should first try to improve the quality of the attributes with low performance, then try to maintain the quality of the attributes with high performance; on the other hand, for the attributes with the same performance level (low performance or high performance), the attribute priority order of allocation resources is: basic attributes, performance attributes and excitement attributes. Combining the above two aspects, the attribute priority order of allocation resources in AIPA is: $LB \succ LP \succ LE \succ HB \succ HP \succ HE$.

4. Results and discussions

4.1. *Verifying whether the asymmetric relationship between AP and CS varies across different types of hotels*

According to the process of PRCA in Section 3.2, the PRCA was respectively conducted on the data concerning the three types of hotels to verify whether the asymmetric relationship between AP and CS varies across hotel types. The results of PRCA concerning the three types of hotels are given in Table 2.

All the regressions of the three types of hotels are significant according to the high value of *F*-statistics (25725.44, 92394.75 and 166646.83), which are all highly significant at 1 percent level (as the asterisk next to each of them shows). The values of R^2 concerning the three types of hotels are also high (0.746, 0.691 and 0.678), which are all highly significant at 1 percent level (as the asterisk next to each of them shows). The twelve dummy variables of the six attributes concerning the three types of hotels (i.e., economy hotel, midscale hotel and luxury hotel) could explain 74.6%, 69.1% and 67.8% variability in the CS of economy hotel, midscale hotel and luxury hotel, respectively. In addition, the variable inflation factor (VIF) is used to check whether there is multi-collinearity between the independent variables in the

Table 2
The results of PRCA concerning the three types of hotels.

Attribute	Economy hotel			Midscale hotel			Luxury hotel		
	Regression coefficients		VIF	Regression coefficients		VIF	Regression coefficients		VIF
Location	β_{lp}^{i}	−0.062*	1.145	β_{lp}^{i}	−0.221*	1.14	β_{lp}^{i}	−0.278*	1.106
	β_{hp}^{i}	0.162*	1.221	β_{hp}^{i}	0.183*	1.211	β_{hp}^{i}	0.141*	1.184
Cleanliness	β_{lp}^{i}	−0.398*	2.227	β_{lp}^{i}	−0.351*	1.688	β_{lp}^{i}	−0.328*	1.379
	β_{hp}^{i}	0.316*	1.912	β_{hp}^{i}	0.273*	1.926	β_{hp}^{i}	0.243*	1.928
Rooms	β_{lp}^{i}	−0.798*	2.754	β_{lp}^{i}	−0.628*	2.116	β_{lp}^{i}	−0.552*	1.689
	β_{hp}^{i}	0.279*	1.714	β_{hp}^{i}	0.284*	1.771	β_{hp}^{i}	0.309*	1.862
Service	β_{lp}^{i}	−0.595*	1.965	β_{lp}^{i}	−0.801*	1.628	β_{lp}^{i}	−0.999*	1.407
	β_{hp}^{i}	0.412*	1.736	β_{hp}^{i}	0.396*	1.728	β_{hp}^{i}	0.431*	1.71
Sleep quality	β_{lp}^{i}	−0.433*	1.779	β_{lp}^{i}	−0.581*	1.666	β_{lp}^{i}	−0.562*	1.407
	β_{hp}^{i}	0.227*	1.716	β_{hp}^{i}	0.221*	1.761	β_{hp}^{i}	0.214*	1.807
Value	β_{lp}^{i}	−0.475*	2.347	β_{lp}^{i}	−0.597*	1.954	β_{lp}^{i}	−0.816*	1.687
	β_{hp}^{i}	0.411*	1.573	β_{hp}^{i}	0.315*	1.538	β_{hp}^{i}	0.216*	1.455
(constant)		3.241*			3.364*			3.494*	
R^2	0.746*			0.691*			0.678*		
F	25725.44*			92394.75*			166646.83*		

*p < 0.01.

regression. If the VIF of a variable is greater than ten, then there is evidence for multi-collinearity. In the three regressions in Table 2, the maximum VIF is 2.754 (the first dummy variable of "Rooms" in economy hotel), which is well below the conservative threshold of ten, indicating that multi-collinearity is not a serious problem in this study.

All the regression coefficients of the twelve dummy variables concerning the three types of hotels are all highly significant at 1 percent level (as the asterisk next to each of them shows). According to the obtained regression coefficients and Eq. (2), the IA values of the six attributes concerning the three types of hotels can be calculated. In accordance with the obtained IA values, the categories of the six attributes concerning the three types of hotels can be determined, as shown in Table 3. On the whole, the IA values concerning the six attributes show a downward trend with the improvement of the hotel level, where the AI values of "Location" and "Value" have a larger range of change in different hotel types. The asymmetric effects of "Cleanliness", "Rooms", "Service" and "Sleep quality" on CS do not vary across hotel types, and the four attributes are classified as basic attributes. However, the asymmetric effects of "Location" and "Value" on CS vary across hotel types. Specifically, "Location" is classified as an excitement attribute for economy hotels, is classified as a performance attribute for midscale hotels, and is classified as a basic attribute for luxury hotels. This may be due to the following reason: the distribution of different types of hotels in different area is similar in the collected data, that is, the three types of hotels may exist simultaneously in the same area. As a result, the performance of the three types of hotels in terms of location is similar. However, with the increase of hotel star or hotel price, customers' expectations to hotels will increase (Kashyap & Bojanic, 2000; Voss, Parasuraman, & Grewal, 1998). Therefore, for economy hotels, customers have a lower expectation for location. In other words, they will be very satisfied if the location is good, but will not be dissatisfied if the location is inconvenient. For midscale hotels, customers have a relatively high expectation for location, and they will be satisfied if the hotel location is good and vice versa. For luxury hotels, customers have a high expectation for location. Customers take it for granted that the location of this type of hotel is good, and they will be very dissatisfied if the location is inconvenient.

In addition, "Value" is a performance attribute for economy hotel and is a basic attribute for both midscale hotel and luxury hotel. It should be noted that the classification results of "Value" are consistent with those obtained from previous studies, i.e., "Value" brings dissatisfaction if its performance is poor (basic or performance attribute) (Lu & Stepchenkova, 2012; Mikulić, Krešić, Miličević, Šerić, & Ćurković, 2016; Ramanathan & Ramanathan, 2011; Tontini et al., 2017). However, "Value" will bring satisfaction to customers for economy hotels if its performance is good. On the contrary, "Value" will not bring satisfaction to customers for midscale hotels and luxury hotels even if it performs well. The reasons are as follows: as mentioned above, customers spend less money for economy hotels, so they have lower expectations for the hotels (Kashyap & Bojanic, 2000; Voss et al., 1998). Consequently, the performance of "Value" is likely to exceed customers' expectations, so they will be satisfied. In contrast, customers spend more money for midscale hotel and luxury hotel, thus they have higher expectations for these hotels (Kashyap & Bojanic, 2000; Voss et al., 1998). They take it for granted that these hotels have a good performance of "Value". Therefore, even if "Value" performs well, customers will still not show satisfaction.

4.2. Verifying whether the asymmetric relationship between AP and CS varies across traveler types

As the asymmetric relationship between AP and CS varies across hotel types, we verify whether the asymmetric relationship between AP and CS varies across traveler types for each of the three types of hotels. For this, the travelers for each of the three types of hotels are first classified into two types, i.e., leisure travelers (solo, friends, family and couple) and business travelers (business) according to the travel type. For economy hotels, midscale hotels and luxury hotels, the numbers of the collected data with respect to leisure travelers and business travelers are "94,403 and 10,842", "418,478 and 76,347", and "731,149 and 216,650", respectively. The details are shown in Table 4.

According to the obtained data concerning travel types, the similar analysis process shown in Section 4.1 is carried out to verify whether the asymmetric relationship between AP and CS varies across traveler types. The results concerning the three types of hotels in terms of travel types are given in Table 5. According to the obtained regression coefficients and Eq. (2), the IA values of the six attributes concerning the three types of hotels can be calculated. In accordance with the obtained IA values, the categories of the six attributes concerning the three types of hotels in terms of travel types can be determined, as shown in Fig. 4.

On the whole, the IA difference between leisure travelers and business travelers decreases with the improvement of hotel level. The asymmetric relationship between AP and CS varies across traveler types. Specifically, for economy hotel, "Cleanliness" is classified as a basic attribute and an excitement attribute respectively for leisure travelers and business travelers; "Value" is classified as a performance attribute and a basic attribute respectively for leisure travelers and business travelers; the categories of the remaining four attributes ("Location", "Rooms", "Services" and "Sleep quality") are the same as basic attributes for leisure travelers and business travelers. For midscale hotel, "Location" and "Cleanliness" are classified as basic attributes and performance attributes respectively for leisure travelers and business travelers; the categories of the remaining four attributes ("Rooms", "Services", "Sleep quality" and "Value") are the same as basic attributes for leisure travelers and business travelers. For luxury hotel, only "Cleanliness" is classified as a basic attribute and a performance attribute respectively for leisure travelers and business travelers; the categories of the remaining five attributes ("Location", "Rooms", "Services", "Sleep quality" and "Value") are the same as basic attributes for leisure travelers and business travelers.

It should be noted that most IA values of business travelers are greater than that of leisure travelers. A reasonable explanation for this finding is as follows. A major difference between leisure travelers and business travelers is that leisure travelers' travel expenses are borne by themselves, while business travelers' expenses are borne by their companies. Compared with business travelers, leisure travelers spend their own money on travel, which can be regarded as loss, so they are more critical about the hotel. As a result, they have higher expectations for

Table 3
The categories of the six attributes concerning the three types of hotels.

Attribute	Economy hotel		Midscale hotel		Luxury hotel	
	IA	Category	IA	Category	IA	Category
Location	**0.449**	**Excitement**	**−0.094**	**Performance**	**−0.327**	**Basic**
Cleanliness	−0.114	Basic	−0.124	Basic	−0.148	Basic
Rooms	−0.482	Basic	−0.377	Basic	−0.283	Basic
Service	−0.182	Basic	−0.339	Basic	−0.397	Basic
Sleep quality	−0.312	Basic	−0.448	Basic	−0.448	Basic
Value	**−0.072**	**Performance**	**−0.309**	**Basic**	**−0.582**	**Basic**

Table 4
The data of the three types of hotels concerning travel type.

Hotel type	Travel type	Statistics	OCS	Location	Cleanliness	Rooms	Service	Sleep quality	Value
Economy hotel	Leisure travelers	Mean	3.62	4.26	3.82	3.40	3.76	3.64	3.82
		Variance	1.394	0.852	1.462	1.420	1.478	1.499	1.489
	Business travelers	Mean	3.44	4.10	3.72	3.27	3.57	3.50	3.61
		Variance	1.562	0.962	1.532	1.528	1.576	1.632	1.687
Midscale hotel	Leisure travelers	Mean	3.92	4.34	4.14	3.78	4.01	3.96	3.99
		Variance	1.049	0.763	1.009	1.119	1.148	1.164	1.118
	Business travelers	Mean	3.67	4.16	3.98	3.59	3.80	3.78	3.70
		Variance	1.202	0.875	1.113	1.241	1.263	1.294	1.320
Luxury hotel	Leisure travelers	Mean	4.27	4.46	4.48	4.22	4.31	4.33	4.10
		Variance	0.815	0.643	0.659	0.865	0.911	0.845	0.934
	Business travelers	Mean	4.03	4.31	4.32	4.01	4.13	4.16	3.80
		Variance	0.994	0.757	0.793	1.028	1.074	0.990	1.106

Table 5
The results concerning the three types of hotels in terms of travel types.

Attribute	Regression coefficients	Economy hotel		Midscale hotel		Luxury hotel	
		leisure travelers	business travelers	leisure travelers	business travelers	leisure travelers	business travelers
Location	β^i_{lp}	−0.072*	−0.006*	−0.230*	−0.195*	−0.296*	−0.240*
	β^i_{hp}	0.162*	0.149*	0.182*	0.171*	0.139*	0.136*
Cleanliness	β^i_{lp}	−0.422*	−0.233*	−0.369*	−0.290*	−0.337*	−0.311*
	β^i_{hp}	0.317*	0.315*	0.272*	0.282*	0.237*	0.258*
Rooms	β^i_{lp}	−0.804*	−0.763*	−0.630*	−0.621*	−0.546*	−0.564*
	β^i_{hp}	0.280*	0.268*	0.282*	0.302*	0.305*	0.322*
Service	β^i_{lp}	−0.584*	−0.651*	−0.812*	−0.765*	−1.018*	−0.955*
	β^i_{hp}	0.409*	0.429*	0.391*	0.412*	0.422*	0.458*
Sleep quality	β^i_{lp}	−0.432*	−0.436*	−0.584*	−0.570*	−0.564*	−0.560*
	β^i_{hp}	0.223*	0.264*	0.214*	0.260*	0.205*	0.242*
Value	β^i_{lp}	−0.458*	−0.576*	−0.569*	−0.662*	−0.808*	−0.812*
	β^i_{hp}	0.407*	0.445*	0.309*	0.342*	0.212*	0.224*
(constant)		3.247*	3.193*	3.382*	3.284*	3.525*	3.415*
R^2		0.745*	0.750*	0.689*	0.692*	0.674*	0.681*

*$p < 0.01$.

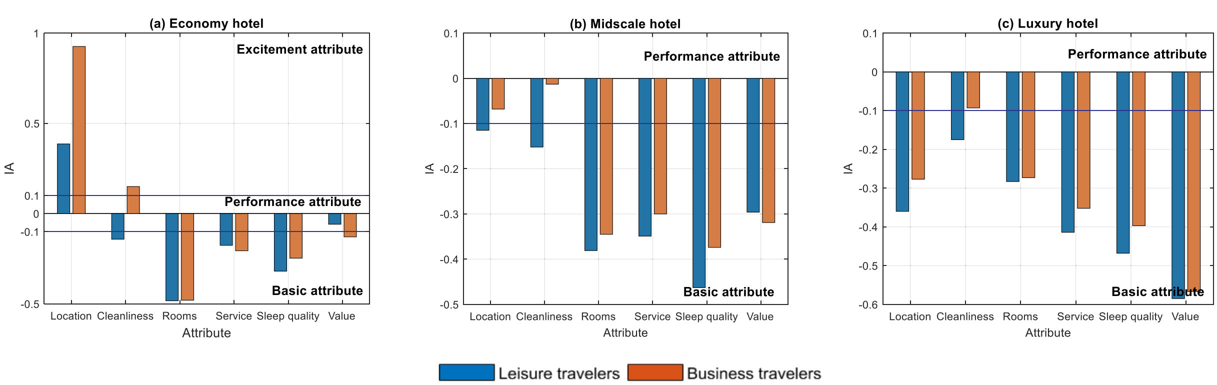

Fig. 4. The categories of the six attributes concerning the three types of hotels in terms of travel types.

hotels. Therefore, the IA value of leisure travelers is relatively lower under the same level of hotel performance. Specially, for economic hotels, the IA value of business travelers about "Value" is lower than that of leisure travelers. "Value" is a basic attribute for business travelers and a performance attribute for leisure travelers. This may be due to the following reasons: the performance of the other five attributes can be directly perceived. Unlike the other five attributes, "Value" is a complex and comprehensive attribute, whose performance is usually determined by comparing the perceptions of the performances of other attributes with the actual price (Kashyap & Bojanic, 2000; Ramanathan & Ramanathan, 2011). Studies have shown that business travelers' performance perception toward hotel attributes is lower than that of leisure travelers' (Lewis, 1984). In other words, for the same hotel attribute, business travelers are more likely to give a lower satisfaction score than leisure travelers (Radojevic et al., 2018). Although business travelers may not have high expectations for economic hotels about "Value", they may have a relatively lower perception of the performance toward "Value", thus "Value" is a basic attribute for business travelers.

4.3. *Verifying whether the asymmetric relationship between AP and CS varies across travelers from different regions*

As the asymmetric relationship between AP and CS varies across hotel types, we verify whether the asymmetric relationship between AP and CS varies across travelers from different regions for each of the three types of hotels. For this, according to the traveler's nationality, the travelers for each of the three types of hotels are first classified into six categories, i.e., Africa, South America, Asia, Oceania, Europe and North America. For economy hotel, midscale hotel and luxury hotel, the numbers of the collected data with respect to travelers from Africa, South America, Asia, Oceania, Europe and North America are "869, 7,424, 13,014, 4,488, 64,011 and 15,439", "3,939, 48,303, 71,933, 25,548, 271,335 and 73,767", and "9,748, 41,679, 142,566, 62,624, 522,254 and 168,928", respectively. The details are given in Table 6.

According to the obtained data concerning travelers from different regions, the similar analysis process shown in Section 4.1 is carried out to verifying whether the asymmetric relationship between AP and CS varies across travelers from different regions. The results concerning the three types of hotels in terms of travelers from different regions are respectively given in Table 7, Table 8 and Table 9.

According to the obtained regression coefficients and Eq. (2), the IA values of the six attributes concerning the three types of hotels can be calculated. In accordance with the obtained IA values, the categories of the six attributes concerning the three types of hotels in terms of travelers from different regions can be determined, as shown in Fig. 5.

On the whole, the asymmetric relationship between AP and CS varies across travelers from different regions. The differences of IA among travelers from different regions decrease with the improvement of hotel level. Specifically, for economy hotel, "Location" is classified as a basic attribute for travelers from Africa, is classified as a performance attribute for travelers from Asia and Oceania, and is classified as an excitement attribute for travelers from South America, Europe and North America; "Cleanliness" is classified as a basic attribute for travelers from Africa, South America, Asia and Oceania, and is classified as a performance attribute for travelers from Europe and North America; "Rooms" is classified as a performance attribute for travelers from Africa, and is classified as a basic attribute for travelers from South America, Asia, Oceania, Europe and North America. "Value" is classified as a basic attribute for travelers from Africa, South America, Asia, Oceania and North America, and is classified as a performance attribute for travelers from Europe; the categories of the remaining two attributes ("Services" and "Sleep quality") are the same as basic attributes for travelers from different regions. For midscale hotel, "Location" is classified as a basic attribute for travelers from Asia and Oceania, and is classified as a performance attribute for travelers from Africa, South America, Europe and North America; "Cleanliness" is classified as a basic attribute for travelers from Africa, South America, Asia and Europe, and is classified as a performance attribute for travelers from Oceania and North America; the categories of the remaining four attributes ("Rooms", "Services", "Sleep quality" and "Value") are the same as basic attributes for the travelers from different regions. For luxury hotel, "Location" is classified as a basic attribute for travelers from South America, Asia, Oceania, Europe and North America, and is classified as a performance attribute for travelers from Africa; the categories of the remaining five attributes ("Cleanliness", "Rooms", "Services", "Sleep quality" and "Value") are the same as basic attributes for the travelers from different regions.

4.4. *What are the priorities of hotel attributes for each type of hotel with respect to different types of travelers and travelers from different regions?*

4.4.1. *The priorities of hotel attributes for each type of hotel with respect to different types of travelers in improving the quality of attributes*

The mean of the ratings with respect to each attribute can be regarded as the performance of each attribute. According the means of the ratings in Table 4 and the IA values in Fig. 4, the AIPA plots for

Table 6
The data of the three types of hotels concerning travelers from different regions.

Hotel type	Regions	Statistics	OCS	Location	Cleanliness	Rooms	Service	Sleep quality	Value
Economy hotel	Africa	Mean	3.8	4.26	4.03	3.59	3.93	3.79	3.94
		Variance	1.255	0.922	1.189	1.302	1.298	1.363	1.365
	South America	Mean	3.69	4.35	3.88	3.51	3.87	3.85	3.91
		Variance	1.145	0.715	1.238	1.203	1.242	1.246	1.229
	Asia	Mean	3.64	4.08	3.74	3.42	3.67	3.62	3.85
		Variance	1.192	0.973	1.238	1.199	1.283	1.263	1.232
	Oceania	Mean	3.72	4.27	3.99	3.51	3.94	3.68	3.92
		Variance	1.385	0.892	1.305	1.383	1.416	1.516	1.45
	Europe	Mean	3.52	4.23	3.73	3.29	3.63	3.55	3.71
		Variance	1.493	0.862	1.576	1.499	1.564	1.597	1.624
	North America	Mean	3.85	4.35	4.09	3.66	4.08	3.81	4.04
		Variance	1.32	0.814	1.274	1.357	1.324	1.435	1.356
Midscale hotel	Africa	Mean	3.85	4.26	4.08	3.74	3.94	3.91	3.87
		Variance	1.118	0.868	1.048	1.154	1.222	1.227	1.275
	South America	Mean	3.89	4.41	4.11	3.85	4	4.09	3.92
		Variance	0.915	0.651	0.924	1.012	1.058	0.995	1.013
	Asia	Mean	3.83	4.17	3.98	3.7	3.82	3.85	3.88
		Variance	0.994	0.888	1.008	1.019	1.122	1.041	1.06
	Oceania	Mean	3.98	4.39	4.23	3.84	4.12	3.99	4.06
		Variance	1.074	0.728	0.962	1.117	1.137	1.193	1.127
	Europe	Mean	3.85	4.3	4.1	3.71	3.95	3.9	3.91
		Variance	1.119	0.786	1.061	1.194	1.193	1.245	1.211
	North America	Mean	4.01	4.42	4.28	3.87	4.19	4	4.09
		Variance	1.109	0.741	0.967	1.14	1.145	1.218	1.14
Luxury hotel	Africa	Mean	4.18	4.42	4.38	4.15	4.22	4.29	3.97
		Variance	0.924	0.668	0.78	0.944	1.052	0.874	1.084
	South America	Mean	4.25	4.48	4.42	4.26	4.29	4.4	4.03
		Variance	0.764	0.635	0.699	0.805	0.869	0.746	0.897
	Asia	Mean	4.14	4.32	4.33	4.12	4.13	4.24	3.93
		Variance	0.858	0.738	0.724	0.855	1.016	0.81	0.953
	Oceania	Mean	4.29	4.52	4.51	4.26	4.36	4.36	4.14
		Variance	0.802	0.548	0.613	0.831	0.894	0.831	0.907
	Europe	Mean	4.19	4.41	4.43	4.14	4.26	4.27	4.03
		Variance	0.882	0.675	0.707	0.943	0.953	0.917	1.008
	North America	Mean	4.31	4.51	4.55	4.25	4.41	4.36	4.12
		Variance	0.849	0.648	0.627	0.887	0.906	0.882	0.986

Table 7
The results concerning the economy hotel in terms of travelers from different regions.

Attribute	Regression coefficients	Economy hotel					
		Africa	South America	Asia	Oceania	Europe	North America
Location	β^i_{lp}	−0.254***	−0.099 (n.s.)	−0.167*	−0.167*	−0.032***	−0.026 (n.s.)
	β^i_{hp}	0.202*	0.146*	0.203*	0.201*	0.158*	0.157*
Cleanliness	β^i_{lp}	−0.314**	−0.413*	−0.428*	−0.361*	−0.403*	−0.361*
	β^i_{hp}	0.232*	0.296*	0.260*	0.283*	0.334*	0.319*
Rooms	β^i_{lp}	−0.298**	−0.872*	−0.675*	−0.733*	−0.822*	−0.743*
	β^i_{hp}	0.279*	0.351*	0.266*	0.251*	0.264*	0.308*
Service	β^i_{lp}	−0.824*	−0.638*	−0.758*	−0.607*	−0.559*	−0.614*
	β^i_{hp}	0.336*	0.355*	0.441*	0.459*	0.409*	0.440*
Sleep quality	β^i_{lp}	−0.600*	−0.348*	−0.494*	−0.510*	−0.405*	−0.529*
	β^i_{hp}	0.291*	0.212*	0.241*	0.226*	0.235*	0.205*
Value	β^i_{lp}	−0.825	−0.475*	−0.474*	−0.484*	−0.467*	−0.488*
	β^i_{hp}	0.318	0.373*	0.383*	0.377*	0.432*	0.376*
(constant)		3.378*	3.256*	3.303*	3.233*	3.225*	3.220*
R^2		0.732*	0.680*	0.690*	0.755*	0.755*	0.758*

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

Table 8
The results concerning the midscale hotel in terms of travelers from different regions.

Attribute	Regression coefficients	Midscale hotel					
		Africa	South America	Asia	Oceania	Europe	North America
Location	β^i_{lp}	−0.248*	−0.184*	−0.255*	−0.256*	−0.210*	−0.235*
	β^i_{hp}	0.238*	0.159*	0.205*	0.187*	0.182*	0.194*
Cleanliness	β^i_{lp}	−0.431*	−0.389*	−0.437*	−0.293*	−0.348*	−0.303*
	β^i_{hp}	0.249*	0.219*	0.274*	0.298*	0.277*	0.299*
Rooms	β^i_{lp}	−0.612*	−0.708*	−0.506*	−0.595*	−0.659*	−0.557*
	β^i_{hp}	0.267*	0.343*	0.255*	0.271*	0.280*	0.281*
Service	β^i_{lp}	−0.820*	−0.889*	−0.977*	−0.788*	−0.740*	−0.817*
	β^i_{hp}	0.437*	0.350*	0.409*	0.399*	0.396*	0.431*
Sleep quality	β^i_{lp}	−0.510*	−0.441*	−0.505*	−0.632*	−0.592*	−0.610*
	β^i_{hp}	0.207*	0.246*	0.201*	0.183*	0.231*	0.212*
Value	β^i_{lp}	−0.524*	−0.629*	−0.578*	−0.600*	−0.595*	−0.605*
	β^i_{hp}	0.287*	0.248*	0.311*	0.309*	0.330*	0.308*
(constant)		3.360*	3.394*	3.415*	3.371*	3.352*	3.302*
R^2		0.700*	0.633*	0.648*	0.714*	0.701*	0.720*

*$p < 0.01$.

economy hotel, midscale hotel and luxury hotel with respect to different types of travelers can be obtained, as shown in Fig. 6, Fig. 7 and Fig. 8, respectively. According to the obtained AIPA plots, the attribute priority order of allocation resources for economy hotel, midscale hotel and luxury hotel with respect to different types of travelers can be determined, as shown in Table 10. In Table 10, the attributes in bold type indicate that the attributes have a low performance, and should be improved first.

It can be seen from Table 10, for the same type of hotel, attribute priority orders of allocation resources with respect to leisure travelers and business travelers are similar but not exactly the same. For the same type of traveler, the differences in attribute priority orders of allocation resources among economy hotel, midscale hotel and luxury hotel are relative large. In addition, “Rooms” and “Location” are the most important and unimportant attributes for both economy hotel and midscale hotel; whereas “Value” and “Cleanliness” are the most important and unimportant attributes for luxury hotel. The prioritization of “Value” increases as the level of the hotel increases.

4.4.2. The priorities of hotel attributes for each type of hotel with respect to travelers from different regions in improving the quality of attributes

According the means of the ratings in Table 6 and the IA values in Fig. 5, the AIPA plots for economy hotel, midscale hotel and luxury hotel with respect to travelers from different regions can be obtained, as shown in Fig. 9, Fig. 10 and Fig. 11, respectively. According to the obtained AIPA plots, the attribute priority order of allocation resources for economy hotel, midscale hotel and luxury hotel with respect to travelers from different regions can be determined, as shown in Table 11. In Table 11, the attributes in bold type indicate that the attributes have a low performance, and should be improved first. It can be seen from Table 11, for the same type of hotel, attribute priority orders of allocation resources with respect to travelers from different regions are different. For the travelers from the same region, the differences in attribute priority orders of allocation resources among economy hotel, midscale hotel and luxury hotel are relative large.

For economy hotel, travelers from Asia and Europe have the similar preference related to hotel attributes, and improving the qualities of “Rooms”, “Sleep quality” and “service” can effectively increase the satisfaction of the travelers from Asia and Europe; travelers from

Table 9
The results concerning the luxury hotel in terms of travelers from different regions.

Attribute	Regression coefficients	Luxury hotel					
		Africa	South America	Asia	Oceania	Europe	North America
Location	β^i_{lp}	−0.158*	−0.363*	−0.262*	−0.177*	−0.290*	−0.271*
	β^i_{hp}	0.139*	0.140*	0.145*	0.133*	0.139*	0.158*
Cleanliness	β^i_{lp}	−0.466*	−0.404*	−0.383*	−0.313*	−0.327*	−0.280*
	β^i_{hp}	0.234*	0.195*	0.228*	0.245*	0.246*	0.282*
Rooms	β^i_{lp}	−0.413*	−0.594*	−0.513*	−0.593*	−0.572*	−0.492*
	β^i_{hp}	0.278*	0.333*	0.295*	0.295*	0.313*	0.301*
Service	β^i_{lp}	−0.969*	−0.945*	−1.205*	−1.058*	−0.941*	−0.956*
	β^i_{hp}	0.441*	0.384*	0.432*	0.438*	0.429*	0.458*
Sleep quality	β^i_{lp}	−0.499*	−0.501*	−0.513*	−0.545*	−0.575*	−0.563*
	β^i_{hp}	0.244*	0.240*	0.193*	0.211*	0.217*	0.215*
Value	β^i_{lp}	−0.824*	−0.801*	−0.780*	−0.789*	−0.832*	−0.794*
	β^i_{hp}	0.219*	0.177*	0.213*	0.190*	0.231*	0.194*
(constant)		3.497*	3.544*	3.549*	3.514*	3.484*	3.427*
R^2		0.693*	0.644*	0.643*	0.680*	0.703*	0.701*

*$p < 0.01$.

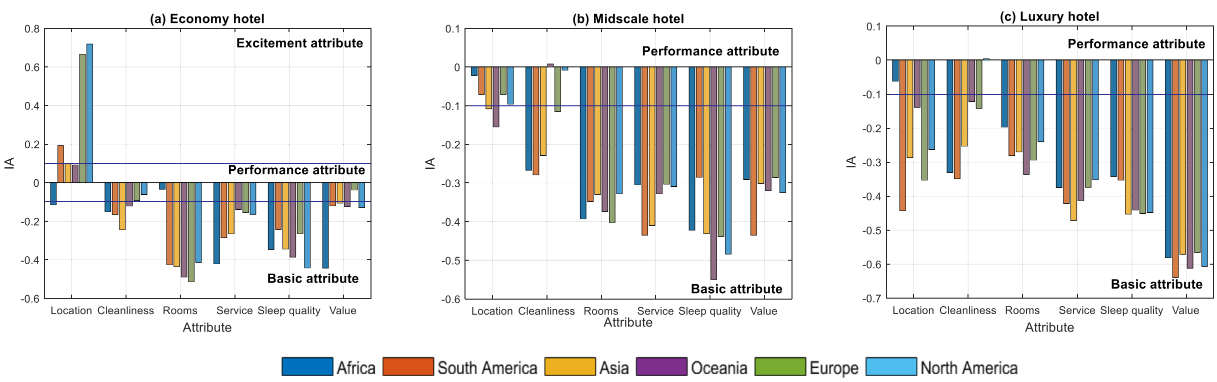

Fig. 5. The categories of the six attributes concerning the three types of hotels in terms of travelers from different regions.

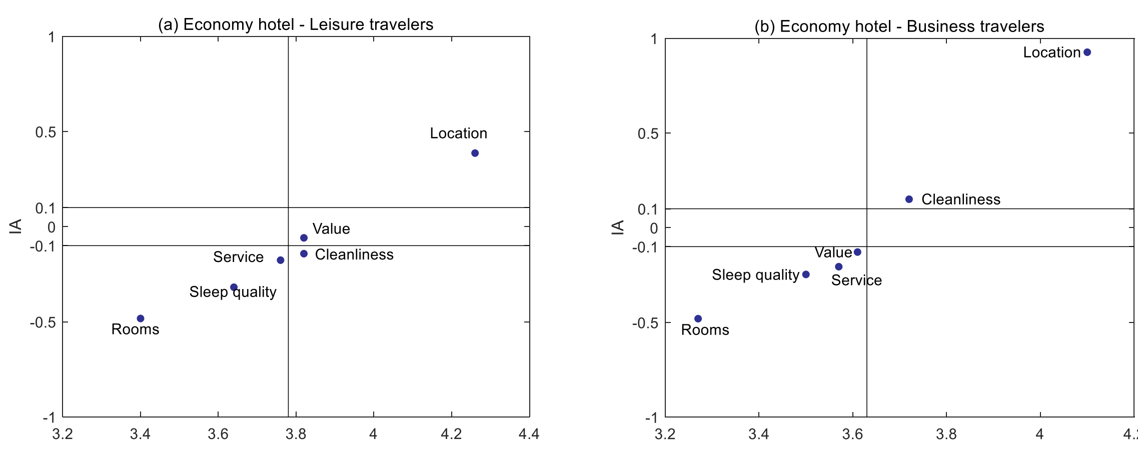

Fig. 6. The AIPA plot for economy hotel concerning leisure travelers and business travelers.

Oceania and North America have the similar preference to hotel attributes, and improving the qualities of "Rooms" and "Sleep quality" can effectively increase the satisfaction of the travelers from the two regions; for travelers from Africa, "Sleep quality" and "Rooms" need to be improved; to increase the satisfaction of the travelers from South America, "Cleanliness", "Service", "Rooms" and "Sleep quality" need to be considered.

For midscale hotel, travelers from Oceania, Europe and North America have the similar preference to hotel attributes, and "Rooms", "Sleep quality" and "Value" are important to increase the satisfaction of the travelers from the three regions; travelers from Africa and South America have the similar preference to hotel attributes, "Rooms", "Value" and "Service" are important to increase the satisfaction of the travelers from the two regions; for Asia travelers, improving the

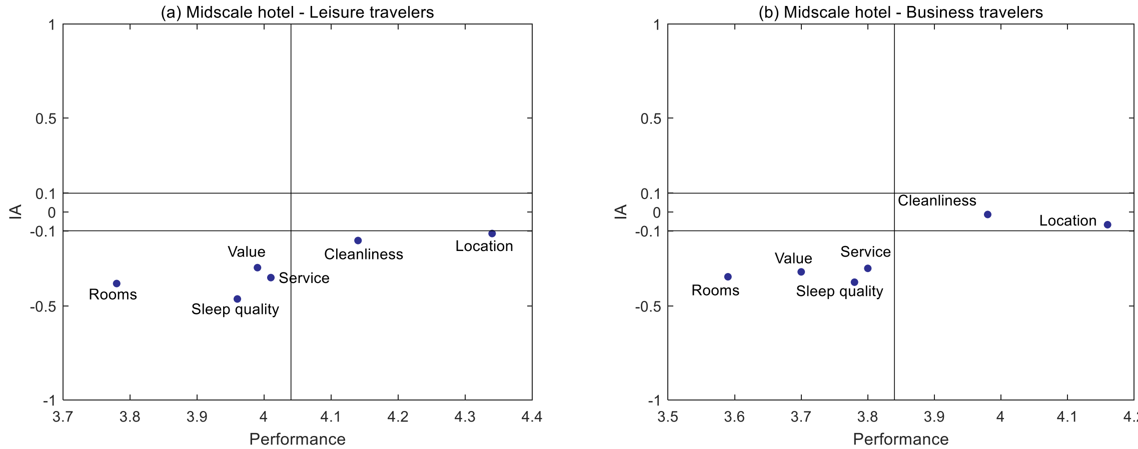

Fig. 7. The AIPA plot for midscale hotel concerning leisure travelers and business travelers.

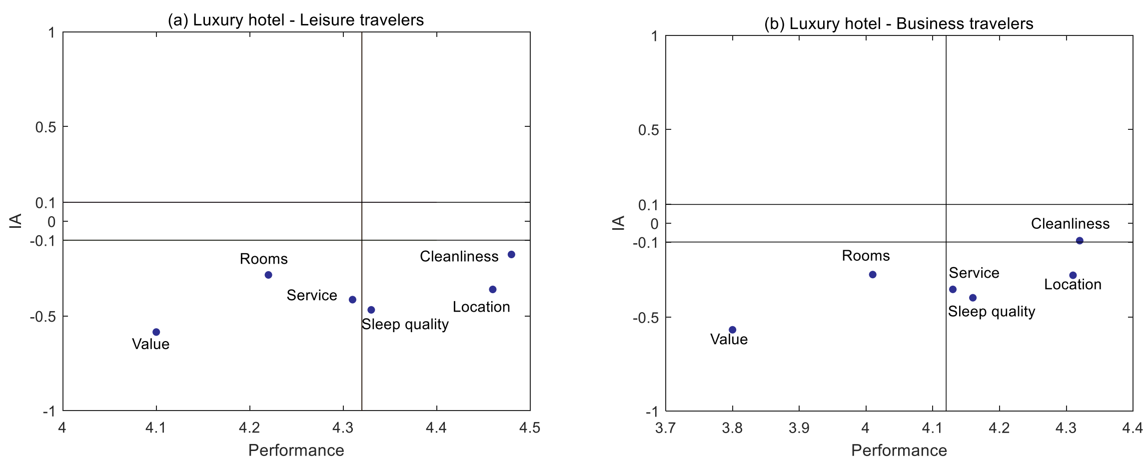

Fig. 8. The AIPA plot for luxury hotel concerning leisure travelers and business travelers.

Table 10
The attribute priority order of allocation resources for different types of hotels concerning different types of travelers.

Hotel type	Travel type	Attribute priority order of allocation resources					
		1	2	3	4	5	6
Economy hotel	Leisure travelers	**Rooms**	**Sleep quality**	**Service**	Cleanliness	Value	Location
	Business travelers	**Rooms**	**Sleep quality**	**Service**	**Value**	Cleanliness	Location
Midscale hotel	Leisure travelers	**Rooms**	**Sleep quality**	**Value**	**Service**	Cleanliness	Location
	Business travelers	**Rooms**	**Value**	**Sleep quality**	**Service**	Cleanliness	Location
Luxury hotel	Leisure travelers	**Value**	**Rooms**	**Service**	Sleep quality	Location	Cleanliness
	Business travelers	**Value**	**Rooms**	Service	Sleep quality	Location	Cleanliness

qualities of “Rooms”, “Service”, “Sleep quality” and “Value” can effectively increase the satisfaction.

For luxury hotel, travelers from Africa, South America, Asia and Europe have the similar preference to hotel attributes, improving the qualities of “Value”, “Rooms” and “Service” can effectively increase the satisfaction; travelers from Oceania and North America have the similar preference to hotel attributes, “Rooms”, “Value” and “Sleep quality” are important to increase the satisfaction of the travelers from the two regions.

5. Conclusion

This study verified the asymmetrical relationship between AP and CS varies across different types of hotels, different types of travelers and travelers from different regions through 1,547,869 user-generated data using PRCA. In addition, to improve customer satisfaction with the limited resources, the improvement strategy of hotel attributes for each type of hotel with respect different types of travelers and travelers from different regions are determined using AIPA.

5.1. Implications

5.1.1. Theoretical implications

In recent years, the literature on CS in the hotel industry has increasingly shown the importance of research on the asymmetric effects of AP on CS (Lai & Hitchcock, 2016; Ramanathan & Ramanathan, 2011). Some scholars have paid attention to this issue and have made some contributions to the research on asymmetric effects of AP on CS in the hotel industry (Albayrak & Caber, 2015; Lu & Stepchenkova, 2012; Matzler et al., 2006; Slevitch & Oh, 2010; Tontini et al., 2017; Xu & Li,

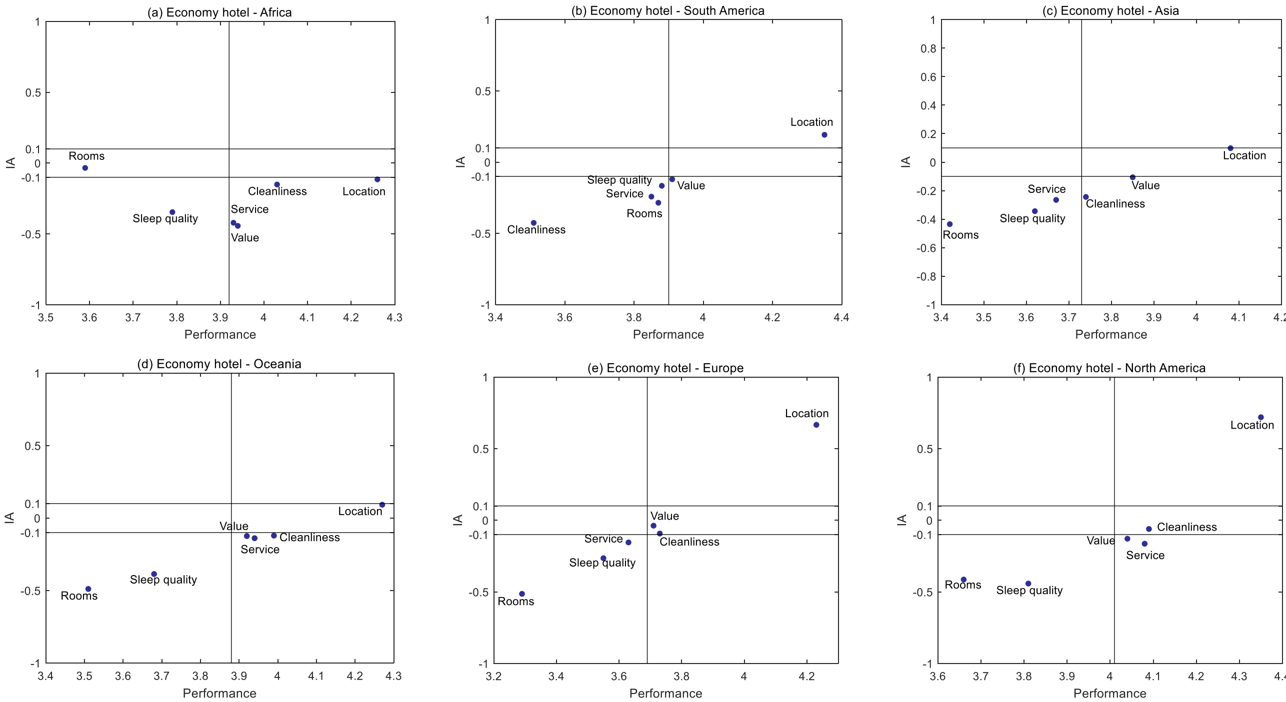

Fig. 9. The AIPA plot for economy hotel concerning travelers from different regions.

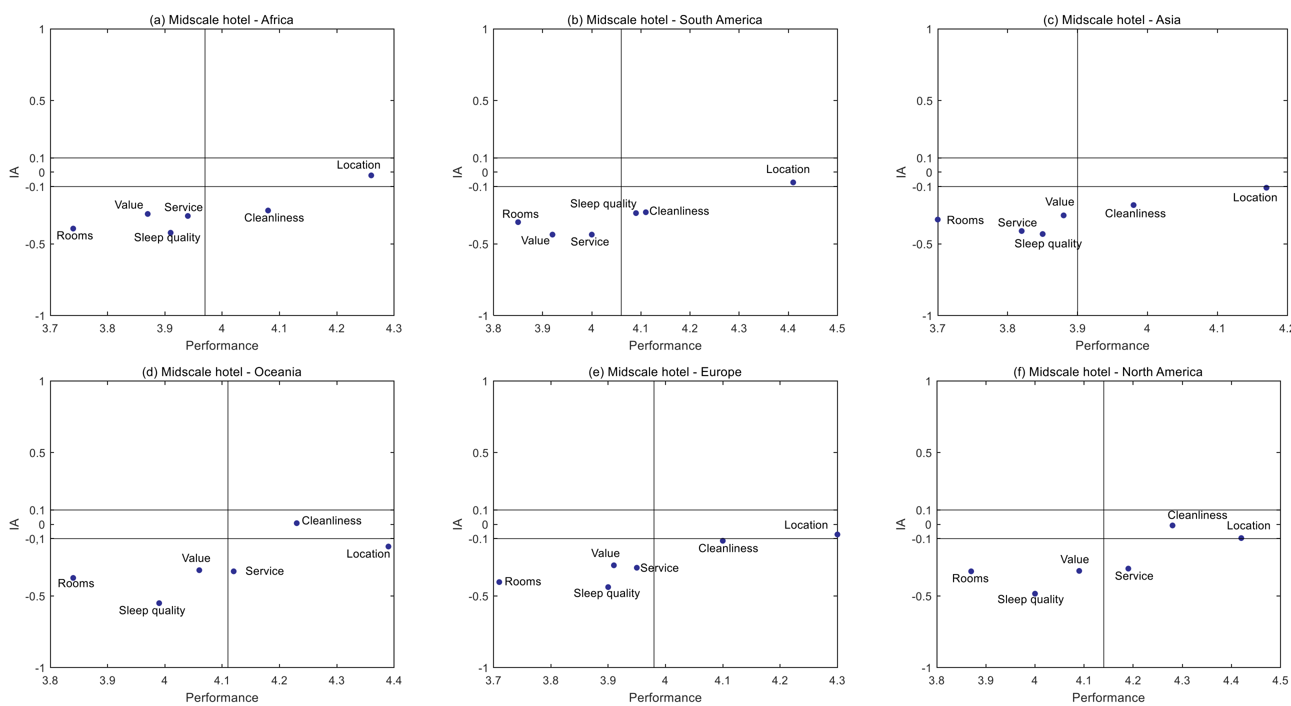

Fig. 10. The AIPA plot for midscale hotel concerning travelers from different regions.

2016; Zhang & Cole, 2016; Zhou et al., 2014). However, these studies mainly focus on the asymmetric effects of AP on CS about a specific market segment from a static point of view. The study on the asymmetric effects of AP on CS concerning different market segments is still rare in the hotel industry. To fill in this research gap, this study explores the asymmetric effects of AP on CS concerning different market segments. The theoretical implications of this study are discussed as follows.

First, based on “big data”, this study provides strong evidence for the existence of asymmetric effects between AP and CS. Although previous studies have investigated the asymmetric effects between AP and CS, they are mainly based on the “small data” of a specific market segment, which restricts the generalizability of their findings (Albayrak & Caber, 2015; Lu & Stepchenkova, 2012; Matzler et al., 2006; Slevitch & Oh, 2010; Tontini et al., 2017; Xu & Li, 2016; Zhang & Cole, 2016; Zhou et al., 2014). By contrast, our findings are based on more than 1.5 million user-generated ratings posted by the travelers from 140 countries concerning 9,596 hotels from 75 capital cities around the world. The large sample (including the hotels of different grades from different

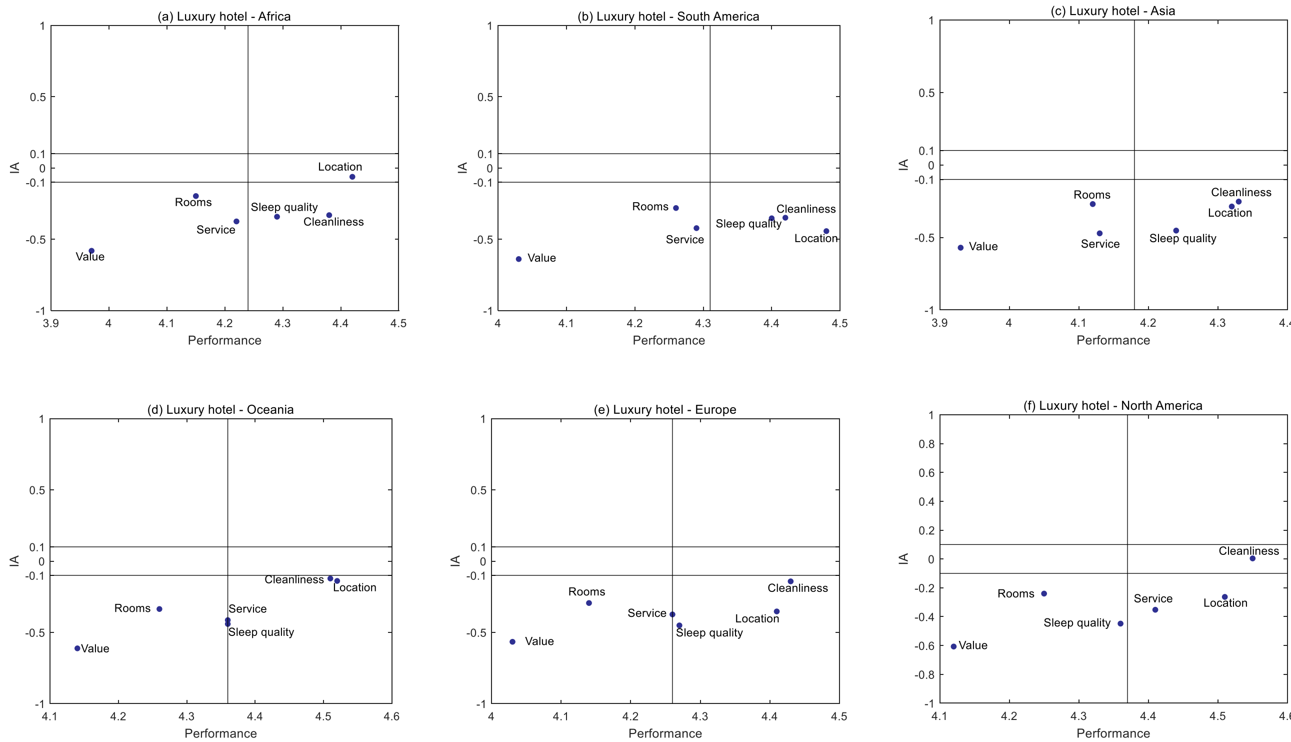

Fig. 11. The AIPA plot for luxury hotel concerning travelers from different regions.

Table 11
The attribute priority order of allocation resources for different types of hotels concerning travelers from different regions.

Hotel type	Regions	Attribute priority order of allocation resources					
		1	2	3	4	5	6
Economy hotel	Africa	**Sleep quality**	**Rooms**	Service	Value	Cleanliness	Location
	South America	**Cleanliness**	**Service**	**Rooms**	**Sleep quality**	Value	Location
	Asia	**Rooms**	**Sleep quality**	**Service**	Cleanliness	Value	Location
	Oceania	**Rooms**	**Sleep quality**	Value	Service	Cleanliness	Location
	Europe	**Rooms**	**Sleep quality**	**Service**	Cleanliness	Value	Location
	North America	**Rooms**	**Sleep quality**	Value	Service	Cleanliness	Location
Midscale hotel	Africa	**Rooms**	**Value**	**Sleep quality**	**Service**	Cleanliness	Location
	South America	**Rooms**	**Value**	**Service**	Sleep quality	Cleanliness	Location
	Asia	**Rooms**	**Service**	**Sleep quality**	**Value**	Cleanliness	Location
	Oceania	**Rooms**	**Sleep quality**	**Value**	Service	Location	Cleanliness
	Europe	**Rooms**	**Sleep quality**	**Value**	**Service**	Cleanliness	Location
	North America	**Rooms**	**Sleep quality**	**Value**	Service	Cleanliness	Location
Luxury hotel	Africa	**Value**	**Rooms**	**Service**	Sleep quality	Cleanliness	Location
	South America	**Value**	**Rooms**	**Service**	Sleep quality	Cleanliness	Location
	Asia	**Value**	**Rooms**	**Service**	Sleep quality	Location	Cleanliness
	Oceania	**Value**	**Rooms**	**Sleep quality**	Service	Cleanliness	Location
	Europe	**Value**	**Rooms**	**Service**	Sleep quality	Location	Cleanliness
	North America	**Value**	**Rooms**	**Sleep quality**	Service	Location	Cleanliness

cities, the diversity of customers with different travel purposes and various cultural backgrounds enhance the generalizability of the results) verifies the existence of asymmetrical relationship between AP and CS.

Second, this study verified the asymmetrical relationship between AP and CS varies across different types of hotels. In the analyzed six attributes, the asymmetric effects of "Cleanliness", "Rooms", "Service" and "Sleep quality" on CS do not vary across hotel types, and the four attributes are classified as basic attributes. However, the asymmetric effects of "Location" and "Value" on CS vary across hotel types. Specifically, "Location" is classified as an excitement attribute for economy hotels, is classified as a performance attribute for midscale hotels, and is classified as a basic attribute for luxury hotels. In addition, the IA values of the six attributes show a downward trend with the improvement of the hotel level, where the IA values of "Location" and "Value" have a larger range of change in different types of hotels.

Third, this study verified the asymmetrical relationship between AP and CS varies across different types of travelers. Specifically, for economy hotels, "Cleanliness" is classified as a basic attribute and an excitement attribute respectively for leisure travelers and business travelers; "Value" is classified as a performance attribute and a basic attribute respectively for leisure travelers and business travelers. For midscale hotels, "Location" and "Cleanliness" are classified as basic attributes and performance attributes respectively for leisure travelers and business travelers. For luxury hotels, only "Cleanliness" is classified as a basic attribute and a performance attribute respectively for leisure travelers and business travelers; the categories of the remaining five attributes are the same for leisure travelers and business travelers.

Fourth, this study verified the asymmetrical relationship between AP and CS varies across travelers from different regions. Specifically, for luxury hotels, "Location" is classified as a basic attribute for travelers from South America, Asia, Oceania, Europe and North America, and is classified as a performance attribute for travelers from Africa. For midscale hotels, "Location" is classified as a basic attribute for travelers from Asia and Oceania, and is classified as a performance attribute for travelers from Africa, South America, Europe and North America; "Cleanliness" is classified as a basic attribute for travelers from Africa, South America, Asia and Europe, and is classified as a performance attribute for travelers from Oceania and North America. For economy hotels, apart from attributes "Services" and "Sleep quality", the categories of the remaining four attributes differ to some extent with regard to travelers from different regions. In addition, the difference of attribute categories decreases with the increase of hotel grade.

Finally, our study validates that different types of hotels should have different strategies for different types of travelers based on big data, and the priorities of hotel attributes for each type of hotel with respect to different types of travelers and travelers from different regions are analyzed by AIPA. The results also indicate that it is necessary to segment the market based on hotel types and traveler types if one wants to precisely understanding travelers' preferences and satisfaction with hotels.

5.1.2. Practical implications

In addition to the theoretical contributions mentioned above, the study offers practitioners a number of managerial insights as discussed below.

First, due to the finding that asymmetrical relationship between AP and CS varies across different types of hotels, different types of hotels should have different strategies to determine the priority of attributes to improve CS with the limited resources. For economy hotels, "Sleep quality" is a basic attribute that customers are more concerned about, and this requirement should be satisfied first. To this end, the economy hotels can take some measures to improve the sleep quality of travelers, such as increasing the sound insulation effect of the room and providing different bedding (such as pillows) for travelers to choose. For luxury hotels, "Value" is a basic attribute with a lower performance that has a great potential to lead to traveler dissatisfaction. As stated in Ramanathan and Ramanathan (2011), "Value" is a complex attribute that requires effective operational practices to minimize operational costs. To this end, luxury hotels should focus on how to achieve efficient operation to provide the best service at the best possible price. For midscale hotels, both "Sleep quality" and "Value" are basic attributes that should be paid attention to. In addition, "Room" is a basic attribute with relatively low performance for all types of hotels. This attribute has great potential to cause customer dissatisfaction. To reduce customer dissatisfaction, hotel managers should also pay attention to how to improve the quality of rooms, which might include, for instance, reasonable room layout, ensuring the normal use of various facilities and providing easy ways of controlling air conditioning and lights, etc.

Second, hoteliers should distinguish traveler types when understanding customers' preferences and satisfaction or carrying out asymmetric analysis. The results show that not only asymmetric effects but also attribute perception are different with respect to leisure travelers and business travelers. Specifically, for economy hotels, "Value" is more important than "Cleanliness" for business travelers because "Value" is a basic attribute with a relatively low performance. Therefore, for economy hotels with a large number of business travelers, it is more important to improve travelers' satisfaction with value. For midscale hotels, "Sleep quality" is more important than "Value" for leisure travelers because "Sleep quality" performs lower than "Value". Therefore, for midscale hotels with a large number of leisure travelers, "Sleep quality" has a higher priority than "Value" when allocating limited resources. For luxury hotels, "Service" is a basic attributes for both leisure travelers and business travelers, but leisure travelers are less satisfied with it than business travelers. Therefore, for luxury hotels with a large number of leisure tourists, it is necessary to invest in staff training to improve service quality. In addition, a detailed report on the attribute priority orders of allocation resources with respect to leisure travelers and business travelers is provided in Table 10, which can provide valuable references for hotel managers in developing their business strategies with regard to different types of travelers.

Third, hoteliers should distinguish traveler regions (or cultural background) when understanding customers' preferences and satisfaction or carrying out asymmetric analysis. The results show that not only asymmetric effects but also attribute perception are different for travelers from different regions. A detailed report on the categories and performances of the six attributes with respect to traveler regions is provided in Figs. 9–11, which can provide valuable references for hotel managers in developing their business strategies with regard to travelers from these regions. For example, for luxury hotels, "Service" is a basic attribute with a relatively low performance for travelers from Africa, South America, Asia and Europe, thus it is necessary to invest in staff training to improve service quality in order to better meet the needs of travelers from these regions. On the contrary, "Sleep quality" is more important than "Service" for travelers from Oceania and North America, because they think the quality of "Service" relatively good, but the "Sleep quality" is relatively poor. Therefore, to effectively improve the satisfaction of travelers from these regions, measures that can improve the "Sleep quality" of travelers should be considered, such as increasing the sound insulation effect of the room and providing different bedding (such as pillows).

5.2. Limitations

The study also has some limitations, which may serve as avenues for future research. First, although user-generated data have been used as the data source to carry out related research works in the hotel industry in recent years (Hargreaves, 2015; Liu et al., 2017; Radojevic et al., 2018; Radojevic, Stanisic, & Stanic, 2015, 2017; Ramanathan & Ramanathan, 2011; Schuckert et al., 2015; Xu & Li, 2016; Ye et al., 2009; Zhang et al., 2010; Zhang et al., 2011), user-generated data may not provide the whole picture of traveler opinions. The results only relate to those travelers who go online and write reviews or provide online ratings. Therefore, how to obtain and select user-generated data reasonably and improve the typicality and representativeness of user-generated data requires further research. Second, this study only investigates the asymmetrical relationship between AP and CS concerning six attributes ("Location", "Cleanliness", "Rooms", "Service", "Sleep quality" and "Value"). Some other attributes (e.g. "Food", "Check in/out", etc.) could be considered in the future. Third, only the user-generated rating data are used in this study. Correspondingly, a large volume of user-generated reviews are publicly available on the Internet and contain a wealth of valuable information, such as the hotel attributes that travelers care about and their sentiments about these attributes (Bi, Liu, Fan, & Zhang, 2019; Liu, Bi, & Fan, 2017). However, since the hotel attributes involved in different reviews may be different, and the attributes mentioned by travelers in some reviews are less, which makes the structured data transformed from user-generated reviews through feature extraction methods and sentiment analysis methods may be sparse (Bi, Liu, Fan, & Cambria, 2019). This will affect the analysis results about the asymmetric effects of AP on CS to a certain extent. Therefore, user-generated reviews are not used in this study. It should be noted that because the attributes involved in the reviews are more abundant, how to perform the asymmetric effects analysis based on user-generated reviews to obtain the asymmetric effects of more other attributes is a future research direction. Finally, the data used in this study are the six attributes collected from *TripAdvisor*, basically frequencies of single-respondent categorizations. It is hard for hotel management to predict consumer expectation and behavior without demographic information. Therefore, whether this classification results vary significantly within hotel types and in different cities due to property specific provision/non-provision or performance/non-performance needs further verification.

Author contributions

Jian-Wu Bi conceived and designed the study, and took the leading in writing and revising the paper. Yang Liu helped write and revise the paper. Zhi-Ping Fan gave some suggestions for the writing and revision of the paper. Jin Zhang collected and processed the data used in the study. All authors read and approved the manuscript.

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