ORIGINAL RESEARCH

Asymmetrical impact of service attribute performance on consumer satisfaction: an asymmetric impact-attention-performance analysis

Mengqiang Pan[1] · Nao Li[2] · Xiankai Huang[2]

Abstract

Analyzing the asymmetrical effects of service attribute performance on customer satisfaction can identify the different effects of service attributes on overall satisfaction at different levels of performance; it can compensate for the shortcomings of conventional linear regression analysis. Previous research on the asymmetrical relationship between restaurant attribute performance and satisfaction has lacked an assessment of market segmentation differences; it has also adopted an attribute priority division method based on the asymmetrical relationship, ignoring consumers' attention to attributes. This paper presents a method to analyze the asymmetrical impact of service attributes performance on satisfaction based on online reviews. First, the sentiment score of the restaurant attributes were calculated by aspect-based sentiment classification and a clustering algorithm. Second, the asymmetrical influence of attribute performance on satisfaction was explored according to the sentiment score of the attributes. Finally, consumers' attention to attributes was measured according to the frequency of attribute mentions and the priority of attribute promotion was investigated by integrating the asymmetrical impact-attention-performance analysis (AIAPA) model of attention. Based on the analysis of 92,904 online restaurant reviews in Tokyo collected on TripAdvisor using the proposed method, this research founds that the performance of most restaurant attributes has an asymmetrical effect on satisfaction. The asymmetrical effect of restaurant attribute performance on satisfaction varies by seasons and market segments. Using the AIAPA model, this research identifies the attribute priority of different restaurant types in different seasons.

Keywords Asymmetrical influence · Online reviews · Aspect-based sentiment classification · Three-factor theory

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1 Introduction

Food is one factor that attracts tourists to destinations, and food tourism has received increasing academic attention (Ellis et al. 2018). Dining as an important activity in tourism, its satisfaction affects the entire travel experience. Improving the dining experience of tourists at a travel destination can not only improve the tourists' overall travel experience, but also attract more tourists and promote the development of the destination's tourism industry. Conventional satisfaction studies consider that consumer satisfaction is based on perceived quality and expectations. When perceived quality exceeds expectations, consumers feel satisfied. Dissatisfaction occurs when perceived quality is lower than expected (Oliver et al. 1997); attribute performance has a linear relationship with satisfaction. Scholars have increasingly found that the relationship between attribute performance and satisfaction may be asymmetrical: the influence degree of the same attribute on overall satisfaction varies with different attribute performance (Slevitch and Oh 2010; Yuan et al 2018). Under limited resources, analyzing the asymmetrical relationship between restaurant attribute performance and satisfaction has important practical significance for determining attribute priority and maximizing consumer dining satisfaction.

To examine the influence of service attributes on satisfaction, researchers have applied various methods. Examples are as follows: critical incident technique (Flanagan 1954); importance-performance analysis (IPA) (Bi et al. 2019; Jang et al. 2009); impact asymmetry analysis (IAA) (Mikulić and Prebežac 2008); asymmetrical impact-performance analysis (AIPA) (Albayrak 2019); and penalty-reward contrast analysis (PRCA) (Bi et al. 2020). However, these approaches often do not take into account consumers' attention to different attributes when prioritizing the attributes. The review text is generated spontaneously by consumers and they often express their concerns towards certain aspects in their reviews, which opens the possibility for capturing consumers' attention to service attributes. In this study, the AIAPA model is proposed to analyze the asymmetric impact of attribute performance on satisfaction, embedding consumers' attention to attributes when prioritizing attributes. Some studies have applied latent Dirichlet allocation (LDA) (Jia 2020; Zhang et al. 2021) to extract service attributes based on users' online reviews. However, unlike with hotels, restaurants employ many proper nouns (such as the names of dishes) in their services; those nouns tend to be sparsely distributed in users' reviews. Xue and Liu (2020) found that LDA may not capture attribute words with low frequency. For determining attribute sentiment, authors have usually applied a coarse-grained sentence-level sentiment classification algorithm to measure fine-grained attribute sentiment. However, sentence-level sentiment classification leads to inaccuracy when a sentence contains multiple attributes.

This study presents an attribute analysis method based on online reviews to determine the attribute priority of restaurants. It aims to address the following issues: (1) how to extract restaurant attributes in online reviews; (2) how to measure accurately the sentiment of attributes; (3) how to analyze accurately the asymmetrical impact of attribute performance on satisfaction; (4) how to determine attribute priority through that asymmetrical relationship.

2 Literature review

2.1 Attribute extraction and sentiment analysis of online reviews

Customers' overall satisfaction is closely related to the attribute performance of the service or product provided (Bartikowski and Llosa 2004). With respect to restaurants, studies that employed questionnaires or online reviews identified food, service, price, and ambience as the four main factors affecting customers' overall satisfaction (Hyun 2010; Ryu and Han 2010; Yan et al. 2015). Following the rapid development of e-commerce, considerable online review data has appeared on the Internet. By analyzing consumers' online review data, it is possible to determine their real needs (Park et al. 2020) and conduct targeted marketing accordingly (Ringel and Skiera 2016). Online review data usually contain digital ratings and online review texts. Digital ratings can quantitatively reflect consumers' satisfaction with products or services (Anderson and Magruder 2012). Online review texts tend to contain more detailed information than ratings (Lak and Turetken 2014). However, owing to the unstructured characteristics of online reviews, it is difficult to analyze them directly; thus, authors have used the following: manual methods (Pan et al. 2014); business analytics software (Griva et al. 2018); and some topic modeling algorithms (Guo et al. 2017) for text data mining. With the development of natural language processing, studies have increasingly applied sentiment analysis techniques to conduct fine-grained research on online reviews (Gomes and Casais 2018; Rambocas and Pacheco 2018).

Sentiment analysis can help managers determine consumers' views about services or product attributes. Such analysis has been widely applied in satisfaction studies related to tourism, such as with hotels and restaurants (Geetha et al. 2017; Phillips et al. 2017). Park et al. (2016) used SentiStrength 2.2 software to analyze reviews on Twitter of restaurants serving Asian food, and they conducted one-way analysis of variance on analysis results. The authors found that the sentiment score for Chinese restaurants was lower than that of restaurants serving other cuisines. Tian et al. (2021) used LIWC software to calculate the sentiment polarity of review texts combined with topic modeling; they found that "service" topics contained more sentiment words did "food." Pezenka and Weismayer (2020) believed it insufficient simply to identify the sentiment polarity of the review topic. The authors used the RapidMiner studio platform to analyze the aspect sentiment of review texts; they identified differences in the influencing factors of dining experiences between tourists and locals; however, the accuracy of aspect-based sentiment classification was only 61.17%. Some scholars have found that new variables were obtained through text sentiment analysis and other methods during data mining; they applied their results to subsequent econometric models. If the performance of a previous model (such as the sentiment classification model) was poor, it led to significant errors in the subsequent econometric estimates and affected the accuracy of the conclusions (Yang et al. 2018).

In terms of attribute extraction, studies have usually applied the LDA algorithm (Jia 2020), latent semantic analysis algorithm (Xu 2021), or manual

methods (Tian et al. 2021) to extract topic attributes; they then judged the satisfaction with topic attributes according to the digital rating of reviews or combined with the sentiment of review texts. The LDA algorithm is calculated based on word frequency in a document; thus, it is often difficult to cover low-frequency words when extracting attributes (Xue and Liu 2020). Therefore, when developing a theme, some restaurant-specific attribute words may be overlooked. Tang et al. (2019) proposed a joint aspect based sentiment topic (JABST) model to extract attribute and aspect words, but this model is still based on a probability distribution, like LDA, where a large number of sparse proper names contained in restaurant reviews may not be extracted by the model, resulting in low recall for low frequency words. Currently, how to effectively extract the attributes is still a challenge since the aspect words are sparsely distributed in reviews. Further, in sentiment classification, a sentiment dictionary or commercial software methods can calculate only coarse-grained sentence sentiment. Machine learning methods using Naive Bayes have achieved good results in sentiment classification of restaurant online reviews (Sharif et al. 2019). However, although these sentence-level sentiment classification algorithms can calculate the sentiment polarity of sentences more accurately, when sentence-level sentiment analysis technology is used for attribute sentiment calculation in a sentence containing multiple different attributes, e.g., "the red wine was good but the noodles were not," and the overall sentiment polarity of the sentence is negative, the sentiment toward the wine would also be classified as negative. Therefore, the sentiment of attributes calculated by sentence-level sentiment classification models may not be accurate, which results from the nature of sentence-level sentiment classification models themselves. Inaccurate measurement of sentiment polarity affects the credibility of subsequent statistical analysis; how to improve the accuracy of sentiment classification is an urgent problem that needs to be solved.

2.2 Asymmetrical influence of attribute performance on customer satisfaction

Gan et al. (2017) found that food, service, and context were the most important factors influencing star ratings by analyzing restaurant online reviews, followed by price and ambiance. In their study, the relationship between attribute performance and ratings was linear. However, in real life, the relationship between attribute performance and rating may be asymmetric. For example, consumers may be dissatisfied with dirty sheets during their stay, yet they may not be satisfied even if the sheets are perfectly clean. Clearly, bed linen attributes have a greater impact on satisfaction at low performance levels than at high performance levels. There also have an asymmetric relationship between restaurant attribute performance and satisfaction. Exploring the asymmetric relationship between restaurant attributes on satisfaction can help guide restaurant attribute improvement.

Since Kano (1984), researchers have been paying increasing attention to the asymmetrical relationship between attribute performance and satisfaction (Yuan et al. 2018). To examine the asymmetrical impact of service attributes performance
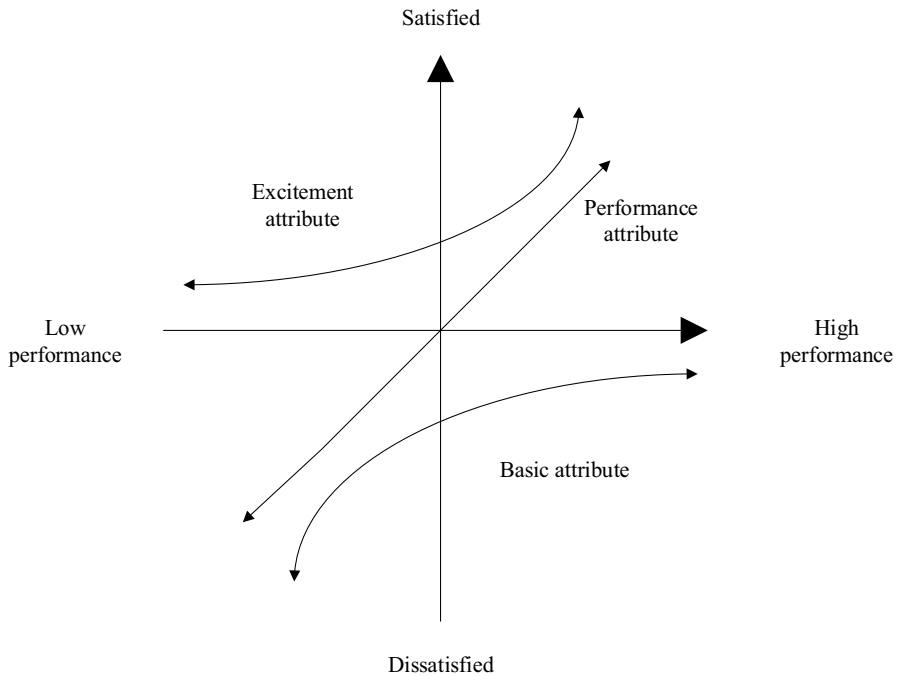
Satisfied

Excitement
attribute

Performance
attribute

Low
performance

High
performance

Basic attribute

Dissatisfied

Fig. 1 Asymmetric influence of attribute performance on satisfaction (adapted from Kano et al. 1984)

on satisfaction, most studies have divided attributes into three categories (Bi et al. 2019): basic attributes, performance attributes, and excitement attributes (Fig. 1).

Basic attributes: If basic attributes do not exceed consumers' expectations, consumers will be dissatisfied; even if those attributes exceed consumers' expectations, consumers may just be neutral. Basic attributes have a greater impact on satisfaction in low performance than in high performance.

Performance attribute: This attribute will produce satisfaction if it exceeds consumers' expectations; it will cause dissatisfaction if it does not exceed expectations.

Excitement attribute: This attribute will produce satisfaction if it exceeds consumers' expectations; but it will not cause dissatisfaction even if it does not exceed their expectations. The excitement attribute has a greater impact on consumer satisfaction in high performance than in low performance.

PRCA is the most common means of distinguishing among basic, performance, and excitement attributes. It defines two dummy variables for each attribute, representing the high-performance and low-performance levels of the attribute. Regression analysis is then conducted to obtain the regression coefficient and significance level of the dummy variables. Finally, the attribute classification is carried out. PRCA can effectively avoid the reliability and validity problems with conventional approaches (Wang et al. 2020). Accordingly, PRCA has been widely applied in tourism research in recent years (Abenoza et al. 2019; Albayrak 2019; Hu et al. 2020; Ju et al. 2019; Lai and Hitchcock 2017). In terms of service attribute improvement, IPA divides attributes into four quadrants, and each quadrant corresponds to
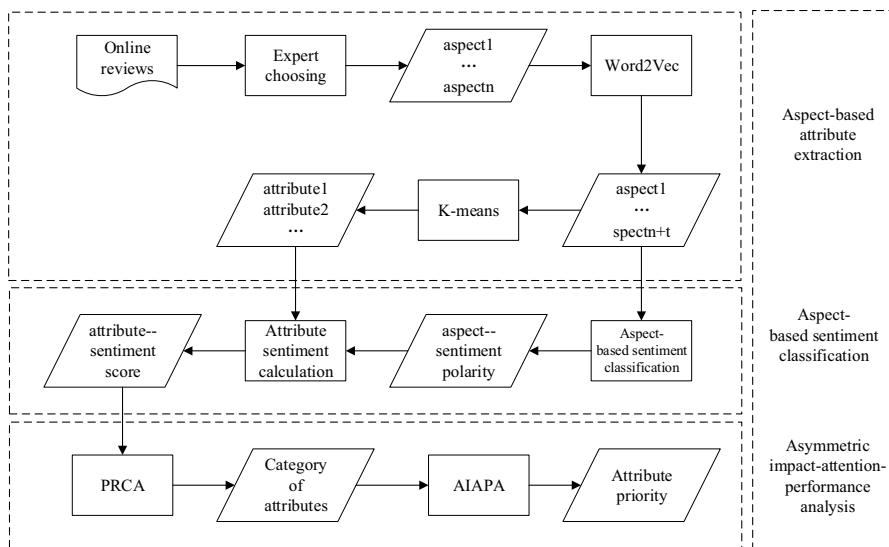
Fig. 2 Research framework

an improvement strategy (Bi et al. 2019; Jang et al. 2009); however, that method can provide only rough suggestions. To overcome this problem, Hu et al. (2020) integrated IAA and IPA; they then proposed asymmetrical impact-sentiment-performance analysis (AISPA) to analyze the asymmetrical relationship between hotel attribute performance and satisfaction and to identify attribute priority. Bi et al. (2020) investigated the asymmetrical relationship between hotel attribute performance and satisfaction using PRCA; they examined the differences in hotel market segments and finally ranked the priority of hotel attributes by AIPA. Then these methods do not take into account the fact that consumers pay different attention to different attributes. Some authors have commented that few studies have dealt with the asymmetrical relationship between hotel attribute performance and satisfaction (Bi et al. 2020); still fewer studies have analyzed the asymmetrical relationship between restaurant attribute performance and satisfaction. Therefore, it is of practical significance to examine the asymmetrical relationship between restaurant attribute performance and satisfaction.

3 Research process

The research framework of this paper appears in Fig. 2; it mainly includes aspect-based attribute extraction, aspect-based sentiment classification, and AIAPA.

3.1 Data collection

We obtained the data from TripAdvisor; there, we collected about 140,000 original reviews related to restaurants in Tokyo. Tokyo is a famous tourist city and has many
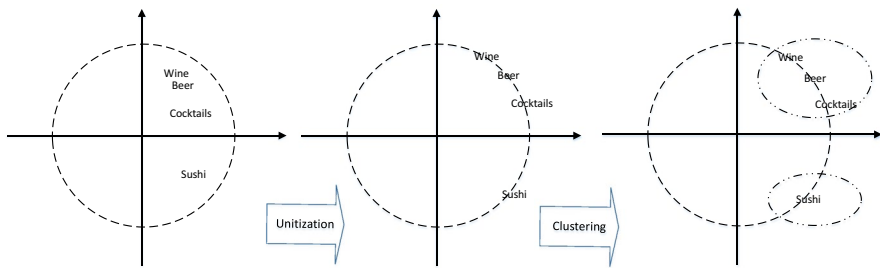
Fig. 3 Unitization and clustering

restaurants offering different national cuisines: it is a good destination for studying tourism and restaurants. What's more, there is a large number of online reviews of restaurants in the Tokyo area on TripAdvisor, which provides the data in this study. Owing to the impact of COVID-19 on travel, all our reviews predated the outbreak of the pandemic: the comments date from October 24, 2008 to March 6, 2020. Each review included the following: restaurant category; restaurant rating; meal rating; meal review text; and mealtime. The review texts had problems related to repetition, deletion, and cross-language, so we conducted the following preprocessing: (1) deleted data with missing review text; (2) deleted reviews not in English. This research obtained 92,904 reviews after preprocessing.

3.2 Aspect-based attribute extraction

We used the aspect-based sentiment classification algorithm to analyze the sentiment score of restaurant attributes. First, we identified the aspect words describing restaurants in the reviews. We selected some aspect words describing restaurant attributes in the reviews by manual screening. To avoid the problem of missing low-frequency words, we expanded the aspect words according to semantic similarity using the Word2Vec algorithm (which helps overcome the problem of data sparsity) after obtaining the aspect words that described the attributes of a restaurant. Using the k-means clustering algorithm, we clustered aspects into different restaurant attributes; we employed aspect words as the input of the aspect-based sentiment classification algorithm to obtain the aspects involved in the review and the corresponding sentiment polarity of those aspects. Finally, we calculated the sentiment scores of each restaurant attribute in the review.

We invited an expert in tourism and one in information technology to choose aspect words related to restaurant attributes according to word frequency. Eventually, the two experts reached consensus on 80 selected aspect words. At the same time, we trained the Word2Vec model using the Tokyo restaurant review data. After the training of Word2Vec, each word in the review could be represented by a 100-dimensional word vector, such as $[x_1, x_2, x_3, …, x_{100}]$. The aspect words selected by the experts were expanded according to semantic similarity, and 113 aspect words describing restaurant attributes were obtained. Finally, we unitized each 100-dimensional word vector. After unitizing the vector representations for the 113 words, we

Table 1 Examples of attribute and aspect words

Attribute	Aspect words
Food	Steak; pasta; pizza; meals; breakfast; tofu; rice; tuna; …
Service	Chef; waiters; staff; serving; waiter; service; …
Drinks	Beer; wine; drink; tea; sake; coffee; …
…	…

Table 2 Model accuracy comparison

Model	Accuracy
TD-LSTM (Jiang et al. 2011)	0.756
LSTM-MATT-AC (Zhi et al. 2019)	0.806
Our model	0.846

applied the k-means algorithm to cluster them. The process of unitization and clustering appears in Fig. 3. We found that a clustering category of 10 could maximize the distinction among different attributes. Thus, we set the clustering category as 10: we used 10 themes to describe restaurant attributes. They were as follows: food, service, queue, drinks, price, menu, dessert, ambience, location and miscellany. Examples of attribute and aspect words can be seen in Table 1.

3.3 Aspect-based sentiment classification

The BERT pre-training model of Google permits a sentiment classification model to be developed based on deep learning that has distinctive absolute advantages. To overcome the shortcomings of previous studies about sentiment classification and attribute extraction, we applied the aspect-based sentiment classification model based on BERT proposed by Zhou et al. (2022); it differs from other models that calculate the attribute and sentiment polarity separately. Our model took both the aspect of the attribute and the comment text as inputs to the neural network; it then outputted the sentiment polarity of the aspect; finally, it calculated the sentiment score of the attribute. The model mainly contained four layers: the BERT, LSTM, IAOA, and Output layers.

1. BERT layer: We used the BERT-Base, Uncased pre-training model provided by Google to obtain the primary representation of the text.
2. LSTM layer: We further extracted the context semantic information of the review texts using the LSTM model.
3. IAOA layer: We employed the IAOA layer to compute the attention weights of the aspects and review texts as new characteristics.
4. Output layer: We used Softmax to classify sentiment polarity.

Table 2 shows the results of a comparison with other aspect-based sentiment classification algorithms. Through comparison with public data sets,[1] it was evident that the accuracy of the algorithm we used was higher than that of other algorithms.

We divided sentiment polarity into three categories: positive, neutral, and negative. We found the accuracy of sentiment classification to exceed 84% through verification with the test set. Finally, we obtained the aspects involved in each review and the corresponding sentiment polarity of aspects, which we represented as 1 for positive, 0 for neutral, and -1 for negative.

3.4 Asymmetrical effects of service attributes on consumer satisfaction

We used PRCA for attribute classification. First, we had to preprocess the data:

1. To avoid data sparsity, we examined only reviews with over two aspect words; we obtained 60,343 review text data.
2. For each review text, if some aspect words among the 113 aspect words describing restaurant attributes appeared in the review, we set the value of those aspects in the review to the sentiment polarity value of the aspect words obtained through the sentiment classification model (i.e., –1, 0, or 1). With other aspects that did not appear in the reviews, indicating that consumers did not make positive or negative comments, we set the sentiment polarity as neutral (i.e., 0).
3. We then calculated the sentiment score of each of the 10 attributes; the attribute sentiment score was the average of the sentiment values of all aspect words contained in the attribute, taking values in the range [–1, 1], as shown in Eq. 1:

$$Attribute_i = \frac{1}{n} \sum_{k=1}^{n} (aspect_{i;k}) \qquad (1)$$

   where $aspect_{i;k}$ denotes the sentiment polarity value of the kth aspect word contained in attribute i.
4. We created two dummy variables for each attribute, representing high- and low-performance level denoted as A$ttribute_i^{high}$ and A$ttribute_i^{low}$, respectively. When the sentiment score of attribute i was greater than 0, we set A$ttribute_i^{high} = 1$ and A$ttribute_i^{low} = 0$. When the sentiment score of attribute i was less than 0, we set A$ttribute_i^{high} = 0$ and A$ttribute_i^{low} = 1$.
5. We calculated the performance level of attributes. Specifically, the performance level of attribute i in review j was recorded as $attribute_{i;j}$; we then calculated the average performance level of attributes $\overline{attribute_i}$ and further determined the average performance level of all attributes $attribute_{total}$. The specific calculation method appears in Eq. 2:

$$
\begin{cases}
attribute_{i,j} = \left(Attribute_{i,j}^{high} - Attribute_{i,j}^{low} \right) \\[2mm]
\overline{attribute}_i = \dfrac{1}{m} \cdot \displaystyle\sum_{j=1}^{m} attribute_{i,j} \\[2mm]
\overline{attribute}_{total} = \dfrac{1}{10} \cdot \displaystyle\sum_{i=1}^{10} \overline{attribute}_i
\end{cases}
\tag{2}
$$

To determine the asymmetrical relationship between restaurant attributes performance and satisfaction, we constructed a dummy variable regression model, as shown in Eq. 3:

$$
OR = \beta_0 \cdot RR + \sum_{i=1}^{10} (\beta_i^{high} \cdot Attribute_i^{high} + \beta_i^{low} \cdot Attribute_i^{low}) + c + err
\tag{3}
$$

where *OR* represents the numerical rating of dining reviews and takes values in the range of [0–5], with 0 representing very poor and 5 excellent; RR represents the overall restaurant rating taking values in the range of [0–5]; C is a constant; *err* is the residual term; and β_i^{high} represents the reward coefficient of attribute *i*. β_i^{low} signifies the penalty coefficient of attribute *i*; it measures the influence of the attribute on overall satisfaction with high and low performance. We determined the classification of basic, performance, and excitement attributes by the satisfaction-generating potential and dissatisfaction-generating potential, usually measured by impact asymmetry (IA) (Mikulić and Prebežac 2008). That mainly includes the following three steps:

1. Calculating the satisfaction-generating potential (SGP). The SGP is the absolute value of the reward coefficient divided by the sum of the absolute values of reward coefficient and absolute values of penalty coefficient, as shown in Eq. 4.
2. Computing the dissatisfaction-generating potential (DGP). The DGP is the absolute value of the penalty coefficient divided by the sum of the absolute values of reward coefficient and absolute values of penalty coefficient, as shown in Eq. 5.
3. Calculating the IA value. The IA value of an attribute is the SGP minus the DGP, as shown in Eq. 6.

$$
SGP_i = \frac{\left| \beta_i^{high} \right|}{\left| \beta_i^{high} \right| + \left| \beta_i^{low} \right|}
\tag{4}
$$

$$
DGP_i = \frac{\left| \beta_i^{low} \right|}{\left| \beta_i^{high} \right| + \left| \beta_i^{low} \right|}
\tag{5}
$$

$$IA_i = SGP_i - DGP_i \tag{6}$$

The classification criteria of the IA value can be defined subjectively; however, we used 0.1 and -0.1 as the cutoff points for the three different categories of factors in line with previous studies (Albayrak 2019; Bi et al. 2020; Mikulić and Prebežac 2008). At those points, when $-0.1 \leq IA_i \leq 0.1$, attribute i is the performance attribute; when $0.1 < IA_i \leq 1$, attribute i is the excitement attribute; and when $-1 \leq IA_i < -0.1$, attribute i is the basic attribute.

AIPA is widely used to determine attribute priority (Albayrak and Caber 2015; Caber et al. 2013). The vertical axis of the AIPA chart is the IA value, and the horizontal axis is the attribute performance, namely attribute$_i$. Two horizontal lines are then drawn with IA$=-0.1$ and IA$=0.1$ as the dividing lines of the three types of attributes; a vertical line is made on the horizontal axis as the dividing line of the attribute performance, and the position of the vertical cutoff line is $\overline{attribute_{total}}$. If $\overline{attribute_i} \leq \overline{attribute_{total}}$, then attribute i is a low-performance attribute; with the reverse situation, attribute i is a high-performance attribute. When prioritizing resource investment, low-performance attributes should be met first. For attributes at the same performance level, the first attribute that should be promoted is the basic attribute; that is followed by the performance attribute and finally the excitement attribute. Basic attributes have a greater potential to make consumers dissatisfied at low performance; thus, the focus should be on low-performance basic attributes.

The AIPA diagram contains only attribute categories and attribute performance levels; it lacks other important information about attributes. Accordingly, Hu et al. (2020) added the sum of the absolute values of reward coefficient and penalty coefficient as the third dimension to assess the impact range of that attribute performance on satisfaction. The original 2-D AIPA chart thus becomes a 3-D AISPA chart. However, in practice, the reward coefficient and penalty coefficient may not both be significant. Thus, an attribute may not have a significant impact on satisfaction at low-performance or high-performance level; simple addition may not accurately represent the impact range of an attribute on satisfaction; and it is difficult to determine attribute priority intuitively using a 3-D graph. To address these problems, this study took consumer attention as an indicator of attribute importance. Unlike with conventional questionnaires, online reviews are a form of spontaneous expression: the greater the attention consumers pay to aspects they perceive, the more will that be reflected in the review text. By counting the frequency of each attribute appearing in the reviews, we ranked the attributes by frequency; we categorized the top five in terms of frequency as high-attention attributes. Likewise, the remaining five became low-attention attributes. To avoid the difficulty in determining attribute priority intuitively with a 3-D graph, our AIAPA diagram was based on the original AIPA diagram: high-attention attributes were represented by plus signs and low-attention attributes by triangles. On the basis of the conventional AIPA prioritization of attributes, high-attention attributes should be promoted first.

Table 3 Dummy variable regression result concerning high and low season

Season	Attribute	$\overline{attribute_i}$	β_i^{high}	p	β_i^{low}	P	IA	Category
High season	Food	0.417	0.247	0.000	−0.550	0.000	−0.381	Basic
	Service	0.183	0.130	0.000	−0.438	0.000	−0.542	Basic
	Queue	−0.017	0.172	0.006	0.074	0.022	0.397	Excitement
	Drinks	0.095	0.141	0.000	−0.414	0.000	−0.491	Basic
	Price	0.014	0.023	0.238	−0.274	0.000	−0.844	Basic
	Menu	0.037	0.111	0.000	−0.440	0.000	−0.599	Basic
	Dessert	0.032	0.078	0.001	−0.371	0.000	−0.653	Basic
	Ambiance	0.108	0.046	0.003	−0.421	0.000	−0.803	Basic
	Location	0.056	0.074	0.000	−0.056	0.000	0.138	Excitement
	Miscellany	0.187	0.089	0.000	−0.346	0.000	−0.589	Basic
	Adjust-R^2=0.2784				n=27,886			
Low season	Food	0.417	0.228	0.000	−0.544	0.000	−0.408	Basic
	Service	0.187	0.133	0.000	−0.435	0.000	−0.533	Basic
	Queue	−0.015	0.120	0.078	0.090	0.006	0.139	Excitement
	Drinks	0.102	0.136	0.000	−0.426	0.000	−0.515	Basic
	Price	0.020	0.061	0.001	−0.241	0.000	−0.593	Basic
	Menu	0.036	0.098	0.000	−0.172	0.000	−0.274	Basic
	Dessert	0.031	0.095	0.000	−0.305	0.000	−0.525	Basic
	Ambiance	0.112	0.049	0.001	−0.427	0.000	−0.794	Basic
	Location	0.066	0.067	0.000	−0.074	0.000	−0.045	Performance
	Miscellany	0.185	0.092	0.000	−0.327	0.000	−0.560	Basic
	Adjust-R^2=0.2779				n=30,777			

4 Results

Yu et al. (2020) found that the dining experience for restaurant customers was affected by the season; however, it has not been confirmed whether the asymmetrical relationship between restaurant attribute performance and satisfaction also varies with the season. Further, owing to differences in the main type of business, prices, and other aspects related to various types of restaurants, consumer expectations may differ for different restaurants; whether the asymmetrical relationship between restaurant attributes performance and satisfaction varies according to market segments has yet to be confirmed. In this paper, we validated these two questions using the methodology presented in Sect. 3, and investigated the attribute prioritization of each restaurant type in different seasons.

4.1 Verify if the asymmetric relationship varies by seasonality

This research counted the number of reviews by dining month from January 1, 2009, to December 31, 2019. We found that the months with the greatest amounts of review data were April, May, October, November, and December. Those times

coincide with the cherry blossom season, autumn leaf season, and Christmas and New Year. Thus, this research defined April, May, October, November, and December as the high season and January, February, March, June, July, August, and September as the low season.

This research conducted PRCA on the data for the high and low seasons. Some of the critical data appear in Table 3: it is evident that most of the dummy variables were statistically significant. The variance inflation factor was less than 2.0, so there was no serious multi-collinearity. Table 3 shows that the absolute values of the reward and penalty coefficients for food attributes were the largest among the coefficients in both the high and low seasons, and they were statistically significant; thus, food attributes were among the most important attributes affecting consumer dining satisfaction. The average performance level of food in both the high and low seasons was 0.417, which was the highest among all the attributes; queue was the only attribute that was less than 0. These findings indicate that most of the sentiment polarity for food in the reviews was positive; sentiment polarity tended to be non-positive for the queue attribute.

From the IA values, it is clear that during the high season, all the attributes were basic attributes; the exceptions were the queue and location attributes, which were excitement attributes. In the low season, the location attribute was a performance attribute, queue was an excitement attribute, and the remaining ones were all basic attributes. The IA value for queue was 0.397 in the high season and 0.139 in the low season: the large difference may have been caused by consumers' expectations for queue and location being lower in the high than in the low season. In summary, the asymmetrical relationship between each restaurant attribute performance and consumer satisfaction varied by season.

4.2 Verify if the asymmetric relationship varies by restaurant type

By comparing high and low season samples, this research found that the asymmetrical relationship between restaurant attributes and consumer satisfaction varied by season. To verify whether the asymmetrical relationship between restaurant attribute performance and consumer satisfaction varied by market segment, this research selected three types of restaurants: those serving Japanese cuisine, those serving American cuisine, and cafés. This research conducted PRCA separately for each restaurant type in the high and low seasons.

Table 4 shows the PRCA results. This research found that the asymmetrical relationship between restaurant attribute performance and satisfaction varied by type of restaurant. During the high season, drinks were an excitement attribute for American cuisine and a basic attribute for the other two restaurant types; location was a performance attribute for Japanese cuisine and an excitement attribute for the other restaurant types. In the low season, queue was a performance attribute for Japanese cuisine and a basic attribute for the other restaurant types; drinks, prices, desserts, and location were performance attributes for American cuisine and basic attributes for the other two restaurant types; menu was an exciting attribute for cafés and a basic attribute for the other two types.

Table 4 Dummy variable regression result concerning three types of restaurant

Season	Attribute	$\overline{attribute}_i$	β_i^{high}	p	β_i^{low}	P	IA	Category
Japanese Cuisine High season	Food	0.467	0.221	0.000	−0.524	0.000	−0.407	Basic
	Service	0.196	0.106	0.000	−0.368	0.000	−0.551	Basic
	Queue	−0.022	0.171	0.016	0.061	0.096	0.471	Excitement
	Drinks	0.064	0.146	0.000	−0.340	0.000	−0.398	Basic
	Price	0.020	0.029	0.236	−0.292	0.000	−0.820	Basic
	Menu	0.037	0.126	0.000	−0.445	0.000	−0.558	Basic
	Dessert	0.021	0.040	0.313	−0.241	0.009	−0.715	Basic
	Ambiance	0.095	0.038	0.067	−0.428	0.000	−0.836	Basic
	Location	0.045	0.061	0.000	−0.066	0.000	−0.041	Performance
	Miscellany	0.195	0.064	0.000	−0.354	0.000	−0.692	Basic
	Adj-R²=0.2422			n=16,049				
Japanese Cuisine Low season	Food	0.478	0.186	0.000	−0.525	0.000	−0.476	Basic
	Service	0.205	0.115	0.000	−0.350	0.000	−0.506	Basic
	Queue	−0.019	0.136	0.076	0.121	0.002	0.056	Performance
	Drinks	0.071	0.129	0.000	−0.239	0.001	−0.298	Basic
	Price	0.026	0.039	0.089	−0.267	0.000	−0.747	Basic
	Menu	0.037	0.095	0.001	−0.160	0.018	−0.254	Basic
	Dessert	0.018	0.082	0.037	−0.064	0.421	0.121	Excitement
	Ambiance	0.095	0.050	0.011	−0.523	0.000	−0.826	Basic
	Location	0.059	0.067	0.000	−0.087	0.000	−0.128	Basic
	Miscellany	0.196	0.066	0.000	−0.335	0.000	−0.672	Basic
	Adj-R²=0.2325			n=17,200				
American Cuisine High season	Food	0.376	0.299	0.000	−0.523	0.000	−0.273	Basic
	Service	0.129	0.213	0.000	−0.549	0.000	−0.440	Basic
	Queue	−0.014	0.178	0.420	0.078	0.579	0.390	Excitement
	Drinks	0.135	0.214	0.000	−0.054	0.749	0.596	Excitement
	Price	−0.002	−0.025	0.778	−0.217	0.014	−0.792	Basic
	Menu	0.028	0.226	0.038	−0.507	0.010	−0.384	Basic
	Dessert	0.048	0.056	0.502	−0.429	0.003	−0.770	Basic
	Ambiance	0.140	0.111	0.059	−0.458	0.009	−0.609	Basic
	Location	0.081	0.080	0.125	−0.012	0.844	0.732	Excitement
	Miscellany	0.132	0.116	0.023	−0.386	0.000	−0.538	Basic
	Adj-R²=0.3061			n=1625				

Table 4 (continued)

Season	Attribute	$\overline{attribute}_i$	β_i^{high}	p	β_i^{low}	P	IA	Category
American Cuisine Low season	Food	0.396	0.295	0.000	−0.641	0.000	−0.369	Basic
	Service	0.159	0.129	0.004	−0.545	0.000	−0.618	Basic
	Queue	−0.013	−0.085	0.763	−0.179	0.229	−0.356	Basic
	Drinks	0.139	0.233	0.000	−0.252	0.067	−0.038	Performance
	Price	−0.018	0.118	0.218	−0.138	0.099	−0.074	Performance
	Menu	0.037	−0.031	0.750	−0.284	0.265	−0.802	Basic
	Dessert	0.053	0.256	0.001	−0.228	0.067	0.057	Performance
	Ambiance	0.168	0.126	0.016	−0.618	0.001	−0.662	Basic
	Location	0.089	0.064	0.190	−0.076	0.206	−0.086	Performance
	Miscellany	0.153	0.117	0.012	−0.308	0.000	−0.449	Basic
	Adj-R²=0.3065			n=1825				
Cafés High season	Food	0.278	0.287	0.000	−0.434	0.000	−0.203	Basic
	Service	0.153	0.208	0.000	−0.572	0.000	−0.467	Basic
	Queue	−0.022	0.061	0.830	−0.029	0.805	0.355	Excitement
	Drinks	0.147	0.158	0.002	−0.524	0.000	−0.536	Basic
	Price	−0.001	0.105	0.297	−0.393	0.000	−0.579	Basic
	Menu	0.040	0.022	0.799	−0.515	0.004	−0.918	Basic
	Dessert	0.077	0.183	0.002	−0.316	0.002	−0.268	Basic
	Ambiance	0.115	0.083	0.142	−0.274	0.076	−0.535	Basic
	Location	0.099	0.128	0.006	−0.075	0.189	0.264	Excitement
	Miscellany	0.154	0.125	0.004	−0.283	0.000	−0.385	Basic
	Adj-R²=0.3306			n=2026				
Cafés Low season	Food	0.273	0.285	0.000	−0.514	0.000	−0.286	Basic
	Service	0.145	0.219	0.000	−0.578	0.000	−0.450	Basic
	Queue	−0.020	0.028	0.917	−0.115	0.323	−0.607	Basic
	Drinks	0.150	0.196	0.000	−0.353	0.001	−0.285	Basic
	Price	0.004	0.094	0.251	−0.354	0.000	−0.580	Basic
	Menu	0.037	0.157	0.070	0.017	0.933	0.807	Excitement
	Dessert	0.070	0.183	0.002	−0.369	0.000	−0.336	Basic
	Ambiance	0.128	0.106	0.042	−0.387	0.014	−0.570	Basic
	Location	0.097	0.079	0.070	−0.108	0.044	−0.152	Basic
	Miscellany	0.156	0.065	0.120	−0.370	0.000	−0.700	Basic
	Adj-R²=0.3474			n=2256				

Overall, among the three restaurant types, the IA values for the queue, food, and location attributes were generally higher in the high than in the low season. This is probably due to the fact that there are more visitors in the high season. Accordingly, visitors may expect that dining requires waiting in line and that locations are difficult to find; thus, their expectations for these attributes are
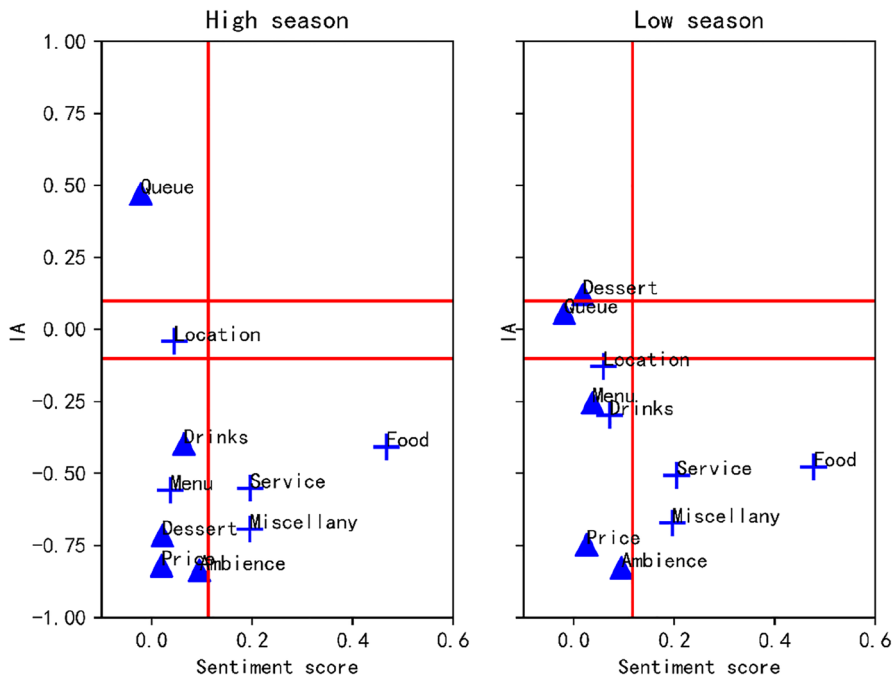
Fig. 4 AIAPA picture of Japanese Cuisine

reduced in the high season. However, during the high season, many visitors go out not only for the food but also to enjoy attractive scenery. In the low season by contrast, tourists may simply want to enjoy the food, and so their expectation for food attributes is higher.

During the high season, the IA values for location and drinks for American cuisine were much higher than with the other two restaurant types. Conversely, the differences for location and drinks among the three types were very small during the low season. This finding shows that customers did not have strong demands for location and drinks attributes when eating American cuisine during the high season. In that season, the IA value for dessert with cafés was higher than with the other two restaurant types, but it was lower than those types in the low season. By contrast, the IA value for menu with cafés was lower than the other two restaurant types in the high season, but it was higher in the low season. In summary, we observed great differences in consumers' expectations for restaurant attributes among the different restaurant types in the high and low seasons. Restaurant managers need to provide consumer satisfaction with respect to their restaurant's circumstances.

4.3 Priorities of attributes for each restaurant type during high and low seasons

According to the method for determining attribute priority using AIAPA described in Sect. 3.4, we prepared AIAPA charts for the three restaurant types using the data
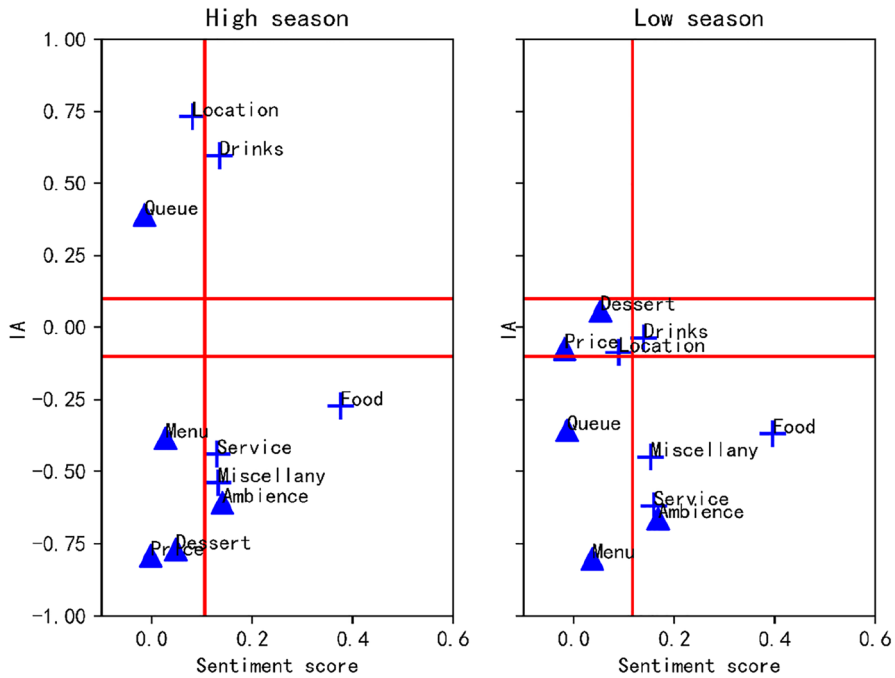
Fig. 5 AIAPA picture of American Cuisine

in Table 4 and the frequency of attributes cited in the reviews. From the AIAPA results, we determined the attribute priority to help restaurant managers assess the priority of attribute promotion and maximize consumer satisfaction.

4.3.1 Japanese cuisine

Figure 4 presents the AIAPA plots for Japanese cuisine. From those AIAPA plots, we observed the following attribute priority order.

During the high season, the attribute priority order of allocation resources for Japanese cuisine was menu, location, service, miscellany, food, dessert, price, drinks, and ambience, queue. Menu and was high-attention, low-performance attributes; thus, it should receive greater attention from restaurant managers.

In the low season, the attribute priority order of allocation resources for Japanese cuisine was drinks, location, service, miscellany, food, price, menu, ambience, queue, and dessert. Location and drinks were high-attention, low-performance attributes; thus, it should receive greater attention from restaurant managers.
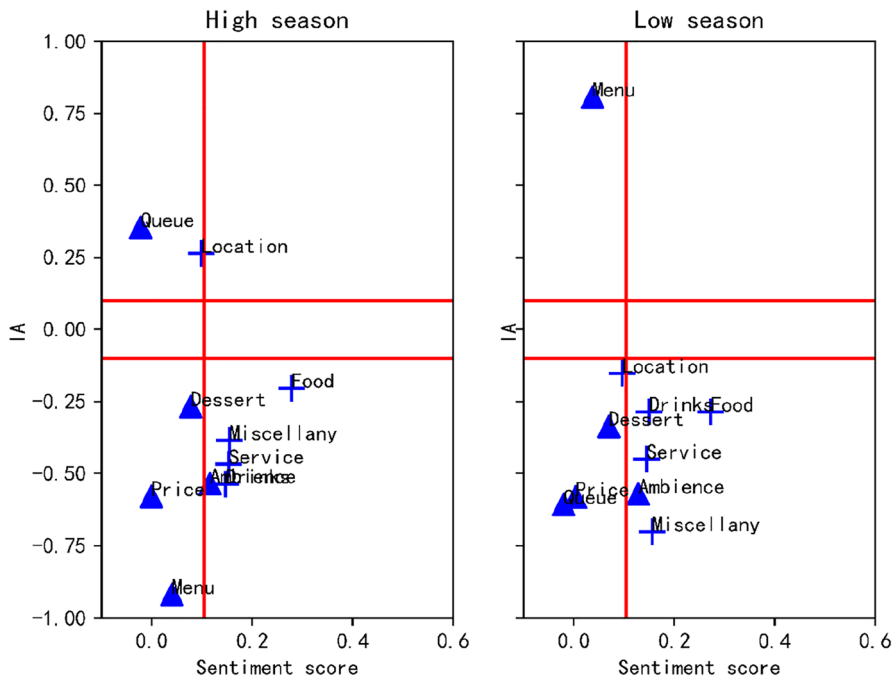
Fig. 6 AIAPA picture of café

4.3.2 American cuisine

Figure 5 presents the AIAPA plots for American cuisine. From those AIAPA plots, we observed the following attribute priority order.

During the high season, the attribute priority order of allocation resources for American cuisine was location, service, miscellany, food, drinks, price, dessert, menu, queue, and ambience. In that season, the high-attention drinks attribute could be improved to enhance its competitive advantage.

In the low season, the attribute priority order of allocation resources for American cuisine was location, service, miscellany, food, drinks, queue, menu, price, dessert, and ambience. Location was a high-attention, low-performance attribute; thus, it should receive greater attention from restaurant managers.

4.3.3 Cafés

Figure 6 presents the AIAPA plots for cafés. From those AIAPA plots, we observed the following attribute priority order.

During the high season, the attribute priority order of allocation resources for cafés was location, drinks, service, miscellany, food, menu, price, dessert, queue, and ambience.

In the low season, the attribute priority order of allocation resources for cafés was location, service, drinks, miscellany, food, queue, price, dessert, menu, and ambience. Location was high-attention, low-performance attribute; thus, it should receive greater attention from restaurant managers.

5 Discussion

This study employed a restaurant attribute analysis method using an aspect-based sentiment classification algorithm and clustering algorithm. We examined the asymmetrical relationship between restaurant attributes performance and consumer satisfaction, and we applied our AIAPA model to determine the attribute priority of different restaurant types in high and low seasons.

First, previous attribute sentiment analysis methods initially determine the sentiment polarity of the sentences in review texts; they then identified attributes contained in the sentences; finally, they identified the sentiment polarity of the attributes. However, such approaches encounter difficulties in the case of multiple attributes contained in the one sentence. Our approach involved a particular number of aspect words having been selected by experts in tourism and information technology; we expanded those aspect words using the Word2Vec algorithm to avoid the problem of overlooking low-frequency words. We then applied the k-means algorithm to cluster the aspect words into attributes. Finally, we used the aspect words as the input for the aspect-based sentiment classification model to directly identify the sentiment of aspects. We calculated the sentiment score of the attributes from the sentiment polarity of the aspect words; in that way, we overcame the shortcomings of sentence-level sentiment classification, which improved the validity of the subsequent statistical analysis results. When the aspect words describing restaurant attributes in online reviews are sparse, the problem of low recall rate of attribute extraction for low frequency words in the methods based on probability distribution is solved by the proposed approach. Conventional sentence-level sentiment classification methods have some defects. However, few studies have employed aspect-based sentiment analysis to study service attributes. To our knowledge, only one report used a paid business platform for aspect-based sentiment analysis; however, its verified accuracy was only 61.17% (Pezenka and Weismayer 2020). Conventional research on service attributes is based on questionnaires: the present study utilized a restaurant attribute analysis method based on online reviews, which can supplement conventional approaches.

Second, in recent years, many studies have examined the asymmetrical impact between service attributes on satisfaction in tourism, but they mainly focused on the hotel industry (Bi et al. 2020; Lai and Hitchcock 2017); few investigations have addressed the asymmetrical relationship between restaurant attributes performance and consumer satisfaction. This research analyzed the asymmetrical relationship between restaurant attributes performance and consumer satisfaction using considerable review data collected by TripAdvisor. This research found that customers' dining experience was affected by seasonality (Yu et al. 2020); the asymmetrical

relationship between restaurant attributes performance and consumer satisfaction differed between high and low seasons. Location attributes were excitement attributes in the high season but performance attributes in the low season. The present study also found that the asymmetrical relationship between restaurant attributes and consumer satisfaction varied by restaurant type: during the high season, drinks and location had different asymmetrical effects on satisfaction with the various restaurant types; during the low season, queue, drinks, price, dessert, menu, and location had different asymmetrical effects on satisfaction with the various restaurant types.

Third, this study identified the priority order of attributes for each restaurant type in different seasons. This research found that the asymmetrical influence of restaurant attributes performance on consumer satisfaction varied by restaurant type and season; thus, it is necessary to determine the attribute priority order for various restaurant types in different seasons. By adding the dimension of consumer attention, the AIAPA method overcomes the shortcomings of the conventional attribute prioritization method (such as AIPA), and can prioritize attributes through a 2-D graph. The comparison shows that food, service, and drinks are the three attributes with the lowest priority in the attribute priorities obtained from the AIPA method, while they are among the high priority attributes in the AIAPA method. This is caused by the fact that the AIPA method does not take into account the consumer's attention to restaurant attributes. The attribute priorities calculated by the AIAPA method seem to be more reasonable.

The findings not only corroborate previous literature, but also find that the importance of restaurant attributes is variable and it is affected by seasonality and restaurant type. Different types of restaurants should focus on different restaurant attributes. In addition, this study uses Word2Vec and K-means algorithm to conduct clustering from the semantic perspective when extracting attributes and can get more segmented restaurant attributes, such as menu, location. Also, the attribute extraction methods used in this paper can be applied to the restaurants where there are a large number of aspects of service which are express by sparse aspect words in online reviews. Unlike other methods that calculate sentence sentiment and infer each of attribute sentiments same as the sentence's sentiment, this research uses a semi-manual method to extract the aspect words describing restaurant attributes and then directly calculates the sentiment polarity of the aspect words without calculating the sentiment of the whole sentence in which the aspect words are located, to improve the accuracy of attribute sentiment calculation. The attribute analysis method proposed in this study can promote the application of big data in tourism, especially in the restaurant industry where aspect words are typically sparse.

6 Conclusion

This study provides some management insights for restaurateurs. As well as conventional questionnaires, restaurant managers can analyze online reviews to determine consumer preferences and make improvement plans. This research found that food is a basic attribute and an attribute with high consumer attention: it is the attribute that can most arouse consumer satisfaction or dissatisfaction. This result confirms

one previous finding, identifying food as one of the most important factors affecting restaurant reviews (Hyun 2010); thus, food attributes warrant additional attention. The quality perceived by diners is also affected by seasonal factors mainly with respect to queue and location: visitors may have greater tolerance for waiting in line in the high season, but queuing may cause greater dissatisfaction in the low season. Thus, if diners have to face long restaurant queues, the management could provide gifts (such as fruit or vouchers) to those waiting in line to reduce their dissatisfaction. Such acts could also improve customer satisfaction with the price attribute, especially in the low season. With regard to the location attribute, managers could provide detailed addresses in websites (such as TripAdvisor) or place prominent signage outside the restaurant. This research also found that different restaurant types should focus on different attributes. For example, service is an important attribute for a café: customers go there not just to enjoy the beverages or food but also to relax and unwind; thus, greater attention should be paid to improving service quality in a café.

The importance of restaurant attributes is dynamic. Restaurants should focus on different restaurant attributes during low and high tourist seasons. The resources of restaurants are often limited, and it could be difficult to improve the performance of all attributes simultaneously. This research applied a restaurant attribute analysis method based on online reviews to determine the priority of resource allocation for various restaurant types in different seasons, thereby allowing managers to improve consumer satisfaction efficiently.

6.1 Limitations and future research

This study applied an aspect-based sentiment classification algorithm to calculate the sentiment of aspect words; and clustered the aspect words into attributes to obtain the sentiment scores of the attributes. The attribute extraction took the form of expert selection plus algorithmic extensions; thus, there was a dependence on manual processing. With improvements in named entity recognition technology, named entity recognition algorithms could be used in future research to extract aspects and attributes automatically from online reviews. This research used data from a single platform (TripAdvisor): whether data from a single platform exerted an impact on the findings of an empirical study should be subjected to further analysis; future empirical comparisons should be conducted using data from different platforms. Finally, the proposed method was applied in restaurants: the applicability to other businesses in tourism and hospitality demands further verification.

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