Which factors influence locals' and visitors' overall restaurant evaluations?

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Abstract

Purpose – Few studies to date have explored factors contributing to the dining experience from a visitor's perspective. The purpose of this study is to investigate whether different restaurant attributes are critical in evaluating the restaurant experience in online reviews for visitors (non-local) and local guests.

Design/methodology/approach – In all, 100,831 online restaurant reviews retrieved from TripAdvisor are analyzed by using domain-specific aspect-based sentiment detection. The influence of different restaurant features on the overall evaluation of visitors and locals is determined and the most critical factors are identified by the frequency of their online discussion.

Findings – There are significant differences between locals and visitors regarding the impact of busyness, payment options, atmosphere and location on the overall star rating. Furthermore, the valence of the factors drinks, facilities, food, busyness and menu found in the reviews also differs significantly between the two types of guests.

Practical implications – The findings of this study help restaurant managers to better understand the different customer needs. Based on the results, they can better decide which restaurant aspects should receive the most attention to ensure that customers are satisfied.

Originality/value – Research on online reviews has largely neglected the role of different visitation motives. This study assumes that the reviews of local and non-local restaurant visitors are based on different factors and separates them to gain a more fine-grained and realistic picture of the relevant factors for each particular group.

Keywords Customer segmentation, Text-mining, Aspect-based sentiment detection, Restaurant reviews

Paper type Research paper

1. Introduction

Dining is one of the most important activities enjoyed while on holiday (Pizam *et al.*, 2004). It is estimated that tourists spend about 25% of their total expenditure on food and beverages (Wilkinson, 2016). As such, food not only contributes economically to tourism destinations, with restaurants comprising important components of tourist attractions (Sparks *et al.*, 2001; Wilkinson, 2016), but can also be the primary motivation to travel, for example, culinary tourism (Getz *et al.*, 2014). According to Stone *et al.* (2019), dining impacts trip satisfaction, intention to return and the likelihood to recommend a destination. Although researchers are increasingly recognizing the important role that food plays in tourism (Lin *et al.*, 2011; Stone *et al.*, 2019), there is relatively scant research focusing on travelers' restaurant experiences. This observation is supported by a meta-analysis conducted by Schuckert *et al.* (2015), which examined 50 articles on online reviews published between 2004 and 2014 and found that only nine articles dealt with restaurants and none of them focused on the traveler's perspective. Also, the literature review of this paper (cf. Section 2.2) reveals that only 3 of 15 studies on restaurant evaluation explicitly deal with tourists' or travelers' evaluations (Erkmen, 2019; Jacobsen and Haukeland, 2002; Vu *et al.*, 2019).

Another critical aspect concerns the source of data used in studies analyzing restaurant experiences. As tourists are increasingly sharing their experiences on review platforms such as TripAdvisor or Yelp, these platforms are a valuable source of information and, thus, are gaining more and more attention in academic research as well as in the tourism industry (Xiang *et al.*, 2017). A considerable proportion of service reviews covers restaurants, with dedicated restaurant review platforms being widely used by both locals and visitors.

These online consumer reviews contain both comments and ratings. Recent research shows that a higher priority is given to ratings rather than text (Aicher *et al.*, 2016). However, the utility of star ratings in general is questionable, given that individual consumers may have different priorities when searching for a restaurant; some restaurant guests may focus on specific food quality, while for others, the atmosphere is more important. These priorities may depend on the main reason for dining-out (June and Smith, 1987). However, the general nature of star ratings makes it difficult for consumers to assess the particular product or service features which are of greatest importance to them. In contrast to online ratings, including star ratings, online reviews are text-based and contain an unrestricted amount of information. The analysis of this information, therefore, recommends sophisticated text-mining tools which go beyond the capabilities of traditional analytical methods (Mellinas and Reino, 2018).

Thus, this investigation uses domain-specific aspect-based sentiment detection to determine the influence of different restaurant features on the overall evaluations. This paper makes two fundamental contributions and differs from previous studies in several respects. First, it is assumed that reviews of locals and non-locals (hereinafter the term visitor is used for non-locals, as it includes all persons visiting a place, for example, tourists and travelers) are based on different factors. In contrast to previous studies (Namkung and Jang, 2008; Zhang *et al.*, 2014), the present study considers both groups separately by introducing a differentiation of visitors and local guests to provide a more fine-grained and realistic picture. One reason for the scarcity of such detailed analyses could be the difficulty in classifying the author of a particular review as either a local or a visitor. Even if the review contains pertinent information about the author's motives for visiting the restaurant, reliable automated classification is often not possible. Only a few researchers use additional information, for example, the distance to the restaurant, to decide whether the reviewer was local or non-local (Vu *et al.*, 2019; White and Buscher, 2012). Second, an extensive literature review is conducted, which illustrates the need for a detailed view on different restaurant guest segments. Research based on online reviews has largely neglected the role of different visitation motives. Furthermore, 14 restaurant attributes (factors) were gleaned from the literature that serve as a basis to identify the most critical factors discussed online. A methodology is proposed that extracts the underlying dimensions of online restaurant reviews and uses a geo-location-based method to differentiate between locals and visitors in online reviews. This approach enables a comprehensive treatment of the following research question:

RQ1. Are there differences between locals and visitors in terms of the importance of restaurant attributes?

The answers to this research question will allow restaurant managers to target their customers, both online and offline, in bespoke fashion by addressing the most important factors for the respective customer segment.

The remainder of the paper is arranged in four sections. Section two provides a literature review which discusses the relevant factors influencing the dining experience in general and from the visitor perspective in particular. It is argued that the importance of restaurant characteristics is highly context-related and that an undifferentiated analysis of all customers is inappropriate: different customer segments have to be considered separately. Section three describes the methodology and Section four provides the results, which, for validation purposes, compare human-based star ratings on TripAdvisor with the machine-derived sentiment polarities of the corresponding review. The influence of 14 restaurant characteristics on the overall evaluation is subsequently determined. Finally, Section five discusses the findings and provides suggestions for future research endeavors.

2. Literature review

2.1 Online reviews

Word of mouth (WOM) has been investigated since the late 1960s and has emerged as a key driver in the consumer decision-making process (East *et al.*, 2008). With the rapid development of Web 2.0 in the intervening years, electronic word-of-mouth (eWOM) has gained a greater scope and impact than traditional WOM (King *et al.*, 2014). One popular form of eWOM is online reviews. As online review sites are in most cases the primary information source for customers, they are facing increasing relevance and popularity and, thus, are continuously growing in both impact and size (Gottschalk and Mafael, 2017).

Previous studies illustrate the significance of online reviews in the travel context (Mellinas and Reino, 2018; Zhao *et al.*, 2015), and there is an increasing number of studies arguing that online reviews influence preferences and affect booking intentions (Gavilan *et al.*, 2018; Xiang *et al.*, 2017). Recent studies further suggest that reviews constitute a rich source of data to extract factors influencing customer evaluation and satisfaction in the tourism domain (Berezina *et al.*, 2016; Guo *et al.*, 2017; Xiang *et al.*, 2017).

In the restaurant sector, studies exploring online restaurant reviews have covered a wide range of topics, for example, the impact of online restaurant reviews on consumer visits and restaurant sales (Lu *et al.*, 2013; Zhang *et al.*, 2014), users' perceptions and evaluations of online reviews (Li *et al.*, 2019; Jeong and Jang, 2011), effects of online reviews on consumers' timing of booking (Zhang *et al.*, 2019) and restaurant features extracted from reviews (Gan *et al.*, 2017; Jeong and Jang, 2011; Pantelidis, 2010; Yan *et al.*, 2015; Zhang *et al.*, 2014).

2.2 Factors influencing restaurants' online evaluations

A meta-analysis on food service selection factors by Medeiros and Salay (2013) revealed that the most important attributes affecting restaurant choice in general are food quality, price, atmosphere and location. Thus, the authors concluded that food-related attributes are key determinants of customer behavior, for example, restaurant choice. However, only a few studies systematically reviewed by Medeiros and Salay (2013) analyzed online reviews.

A more recent meta-study by Gan *et al.* (2017) illustrates that researchers have generally agreed on four factors affecting restaurant choice, namely food, service, atmosphere/ambience and price. In their empirical study, Gan *et al.* (2017) analyzed Yelp review data of restaurants by using sentiment analysis to identify attributes affecting the overall star ratings. They found that food, service, context, price and atmosphere had significant impacts on the overall dining experience evaluation manifested by the overall star ratings.

Zhang *et al.* (2014) also identified food as the most important factor affecting eWOM. The authors analyzed reviews from Dianping.com and found that food taste and price influence both positive and negative eWOM, whereas restaurant environment and service only impact positive eWOM. They concluded that Chinese customers have relatively low expectations regarding employee service, as this aspect is not associated with negative comments. Yan *et al.*'s (2015) study shows different results for the Chinese market, but they looked at the impact on revisitation intention. In this regard, they found that service quality, atmosphere, food quality and price are the primary antecedents (Yan *et al.*, 2015).

These studies add to the studies exhibited in Table 1 that explore the factors influencing the customer's restaurant evaluation in general (Gupta *et al.*, 2007; Hyun, 2010; Jeong and Jang, 2011; Liu and Jang, 2009; Namkung and Jang, 2008; Parsa *et al.*, 2012; Ryu and Han, 2010; Wall and Berry, 2007; Yan *et al.*, 2015; Zhang *et al.*, 2014). Most researchers agree that the overall dining experience is best conceptualized as a function of food, service atmosphere and price, but the importance assigned to these factors differs according to the method used, the geographical area examined and whether a distinction was made between locals and visitors (Table 1). Furthermore, only 3 of 15 studies explicitly deal with visitors' evaluations of restaurants (Erkmen, 2019; Jacobsen and Haukeland, 2002; Vu *et al.*, 2019), and from these, only one study (Vu *et al.*, 2019) uses online reviews.

2.3 Dining-out motives and tourism

As the literature review shows so far, most prior research on online restaurant reviews did not differentiate between reviews written by local people and visitors. However, particularly in the field of tourism, many researchers have emphasized the role of local food and restaurants for tourist destinations (Björk and Kauppinen-Räisänen, 2016; Lin *et al.*, 2011). Sparks *et al.* (2001) identified restaurants as an important aspect of tourist attractions. Even in the majority of cases where food cannot be seen as a primary determinant of destination choice, it nevertheless contributes to the overall holiday experience and, thus, influences satisfaction and evaluation of the holiday experience (Erkmen, 2019; Kivela and Crotts, 2006; Nield *et al.*, 2000).

Although it is assumed that the reason for dining-out is essential for the importance of different factors contributing to the dining experience, relatively few studies have explored the particular factors contributing to visitors' dining experiences (Chang *et al.*, 2012; June and Smith, 1987; Ponnam and Balaji, 2014). For example, Ponnam and Balaji (2014) demonstrate that restaurant attribute evaluations vary across different visitation motives. The authors find that in a casual dining context, there are differences in the perceived importance of restaurant attributes depending on the dining-out occasion (e.g. celebration, take-away, dine out or date). Their results indicate, for example, that gourmet taste and variety-in-menu are important assessment criteria for dine out patrons. Gan *et al.* (2017) even propose context as additional information in online reviews, which they define as "reviewers' personal experiences or anecdotes, which sometimes do not provide information on restaurant quality" (Gan *et al.*, 2017, p. 472). They argue that the context might influence consumers' expectations, and thus, it is particularly important to take this information into

Table 1. Studies analyzing the influence of different factors contributing to overall dining experience

Authors	Attributes	Method	Geographic area	Visitors/Locals
Erkmen (2019)	Cultural aspect of food, service	Questionnaire	Turkey	Visitors
Gan *et al.* (2017)	*Food, service, atmosphere, price*	*Text-mining – online reviews*	*The USA*	*Not differentiated*
Gupta *et al.* (2007)	Food, price and service	Questionnaire	The USA	Not differentiated
Hyun (2010)	Food, service, price, location and atmosphere	Questionnaire	The USA	Not differentiated
Jacobsen and Haukeland (2002)	Atmosphere, food and service	Questionnaire	Norway	Visitors
Jeong and Jang (2011)	Food, service, atmosphere and price	Questionnaire	The USA	Not differentiated
Liu and Jang (2009)	Food, cleanliness, service and price	Questionnaire	The USA	Not differentiated
Namkung and Jang (2008)	Food, atmosphere and service	Questionnaire	The USA	Not differentiated
Pantelidis (2010)	*Food, service, atmosphere, price and menu*	*Manual content analysis – online reviews*	*London*	*Not differentiated*
Parsa *et al.* (2012)	Food, service and atmosphere	Experimental setting and questionnaire	The USA	Not differentiated
Ryu and Han (2010)	Food, service and atmosphere	Questionnaire	The USA	Not differentiated
Vu *et al.* (2019)	*Service, price and atmosphere*	*Text-mining – online reviews*	*Australia*	*Visitors*
Wall and Berry (2007)	Food, atmosphere and service	Experimental setting and questionnaire	The USA	Not differentiated
Yan *et al.* (2015)	*Service, atmosphere, food, price and value*	*Text-mining – online reviews*	*China*	*Not differentiated*
Zhang *et al.* (2014)	*Food, atmosphere, service and price*	*Text-mining – online reviews*	*China*	*Not differentiated*

Notes: Italic indicates studies analyzing online reviews. Grey indicates studies focusing on visitors account. However, only a few review websites such as TripAdvisor.com and Yelp.com provide context information by offering categorizations such as “a good place for [. . .]”.

A very special dining context is that experienced while traveling. According to Kivela and Crotts (2006), travel dining offers a pleasure aspect and represents an important part of the tourist experience. Furthermore, travel dining often fulfills a social function that is different from other contexts of dining, including building new social relations and strengthening social bonds (Fields, 2002). Through food, tourists can engage in new cultural experiences which are different from home. Regarding the factors affecting tourists’ evaluation of the dining experience, Chang *et al.* (2011) identify variety as a key attribute, whereby the quality of the food plays a subordinate role as long as intangible aspects are met. These results are partly confirmed by the study of Erkmen (2019). His survey among foreign travelers visiting the city of Istanbul revealed that the most important factor regarding the dining experience for travelers is the cultural aspect of food, which means that travelers expect local traditional cuisine in terms of the type of food as well as its presentation. Furthermore, social factors including the service quality and the behavior of other customers were found to be relevant for travelers. Food quality and atmosphere were not found to be particularly important for the dining experience of travelers. Jacobsen and Haukeland (2002) also focused on tourists and identified three major factors influencing tourists’ selection of restaurants: ambience of the place, food and service quality. Vu *et al.* (2019) separated the review data for visitors and locals based on the user location indicated on TripAdvisor and examined only the visitor data. Their results indicate preference variations toward cuisine, dish, meal and restaurant features across different visitor groups. The authors considered atmosphere, service and price for their analysis and found that service is the most important restaurant feature for international travelers visiting Australia. However, the study did not include food quality as a restaurant feature, which, according to prior studies, is one of the most important criteria for customer evaluations in reviews (Gan *et al.*, 2017; Pantelidis, 2010; Zhang *et al.*, 2014).

The food aspect seems to play a less important role for tourists than for locals in the evaluation of the dining experience. Only one study focusing on tourists identified food as being the most important factor for the overall dining experience (Gan *et al.*, 2017), whereas nearly all studies, except Yan *et al.* (2015), that used locals as respondents concluded that food is the most influential factor for the dining experience (Table 1). Thus, this leads us to the following hypotheses:

H1. Food has a stronger impact on the overall star rating for locals than for visitors.

Furthermore, as the literature suggests that the motives of tourists to dine out differ significantly from those of locals, it is likely to affect all factors influencing the dining experience. Therefore, this study further proposes:

H2. There is a difference between locals and visitors regarding the valence of reviews discussing different restaurant factors.

H3. There is a difference between locals and visitors regarding positive impacts of restaurant factors mentioned in online reviews on the overall restaurant rating.

H4. There is a difference between locals and visitors regarding negative impacts of restaurant factors mentioned in online reviews on the overall restaurant rating.

Differences are tested between the two groups for the following 14 restaurant factors: food, staff, busyness, cleanliness, reservations, drinks, payment, value, menu, desserts, ambience, facilities, quietness and location.

3. Methodology

The approach at hand uses an automatic method for information extraction, namely sentiment detection (opinion mining for semantic retrieval). Sentiment analysis helps to determine the negative or positive polarity of written text. Alaei *et al.* (2017) give an overview on sentiment analysis within the tourism domain and identify three predominant techniques: machine learning (corpus-based), lexicon-based approaches and hybrid approaches. All three pursue the goal of categorizing text according to its polarity or, more precisely, determining whether the emotion of a piece of text is positive, neutral or negative. Comprehensive overviews of these techniques are also given by Liu (2012) and Pang and Lee (2008).

A literature review conducted by Alaei *et al.* (2017) resulted in six papers applying sentiment analysis on restaurant reviews: two using a lexicon-based approach and four based on machine learning techniques. Only one of these six studies used Tripadvisor data, yet failed to analyze the reviews at the restaurant feature level. Xiang *et al.* (2017) conducted a comparative analysis of three major review platforms, namely Tripadvisor, Expedia and Yelp. The authors found that Yelp has a substantially lower amount of review data and a more polarized overall sentiment distribution. Expedia has a smaller amount of variance of the information contained in the reviews, such that its review topics are rather weak predictors for the rating data, which is especially important for the present study, as the textual content is connected with the overall star rating. In light of these findings, Xiang *et al.* (2017) concluded that Tripadvisor is the premier data source for empirical evidence and is consequently used here.

For some research applications, however, solely identifying the overall polarity is insufficient, as valuable information included in the text can be lost at the aggregated level. To automatically determine the sentiment toward underlying topics, domain-specific aspect-based sentiment detection is used in this study. Aspect-based review mining is well suited to analyzing reviews containing different product or service features. The analysis task is split into two parts, namely the aspect extraction step and the sentiment analysis step.

Here, the raw text was processed through extensions of the text processing operators of the Rapidminer Studio platform (Version 9.3.1). This platform was extended by the AYLIEN text-mining API for natural language processing (NLP) and machine learning-powered tools for analyzing and extracting various kinds of information from text (Version 0.2.0) as well as a text processing package for statistical text analysis and NLP (Version 8.2.0). The AYLIEN text analysis extension uses a hierarchical bidirectional long short-term memory (H-LSTM) and performs competitively in comparison with the state-of-the-art sentiment analysis on several data sets (Ruder *et al.*, 2016a; Ruder and Plank, 2018). The multilingual problem is solved at the same time using a convolutional neural network (CNN) that makes it independent from, for example, sentiment lexica (Ruder *et al.*, 2016b). It takes the sentential context – the interdependencies of sentences – and the structure of reviews into account in two different ways:

1. intra-sentence relations use the relationship between a word and the preceding and successive words at the sentence level; and
2. inter-sentence relations use the relationship between a sentence and the preceding and successive sentences at the review level.

The hierarchical bidirectional LSTM (Bi-LSTM) uses the idea that a reviewer's opinion expressed by a word/sentence will not dramatically change for the next word/sentence, while bidirectionality implies also using preceding information. Finally, the process determines the overall sentiment and an aspect-based sentiment value for each restaurant aspect.

If any 1 of the 14 factors is mentioned in a review and detected by the software, then the polarity of the statement regarding this aspect is evaluated and assigned one of the following values: “−1 negative,” “0 neutral” or “1 positive.” If an item is not detected or mentioned in a certain review, which implies that there is neither a positive nor a negative comment about this aspect, then it was coded as “0 neutral.” Likewise, missing values were replaced by “0 neutral.” This results in 15 different variables: the polarity score of the review as a whole and the aspect-based evaluations of the 14 individual service quality items (food, drinks, staff, facilities, location, quietness, value, cleanliness, payment, menu, desserts, ambience, reservations and busyness). It also reveals the absolute count of the occurrence of each aspect. For validity purposes, the data-driven overall sentiment of a review is cross-tabulated with the reviewers’ overall star rating on TripAdvisor. Finally, the influence of the 14 factors on the overall star rating on TripAdvisor, measured on a scale ranging from “1 worst rating” to “5 best rating,” is determined using linear regression.

4. Results

4.1 Data collection and sample description

In all, 100,831 online reviews for restaurants located in the city of Washington D.C. were automatically retrieved (Churchill, 2019) from the online travel agency (OTA) website, TripAdvisor (www.tripadvisor.com/). The reviewers’ home locations, expressed by their geographical coordinates, were used to calculate the distance of each reviewer to the center of Washington D.C. (latitude: 38.89495° and longitude: −77.03665°). The maximum distance to the city center using the World Geodetic System 1984 (WGS84) ellipsoid was 11,674.53 miles (18,788.33 km). For an overview of the reviewer distances, Figure 1 shows a histogram of the absolute number of reviewers (*y*-axis) along their distances to the city center from 0 to

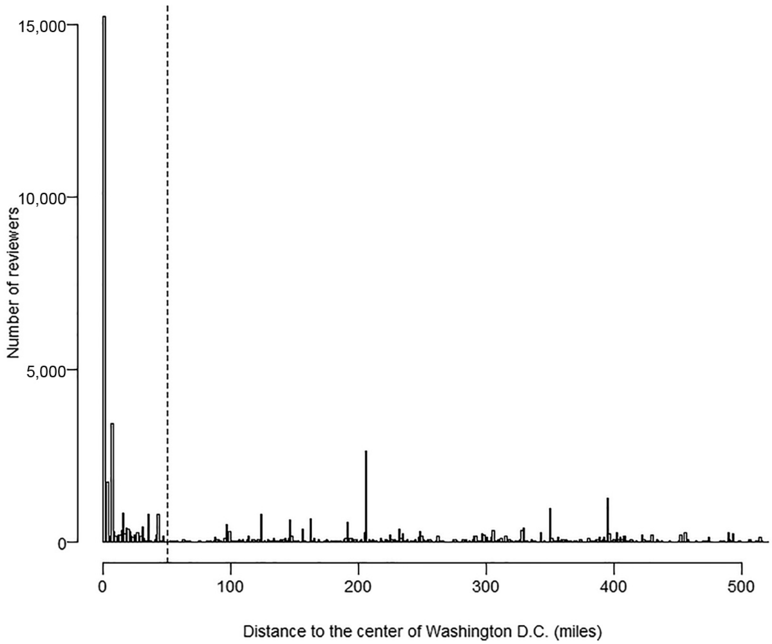

Figure 1.
Reviewer distances

500 miles (804,672 meters) (x-axis). The distance of 50 miles (80,467.2 meters) from the city center is indicated by the dashed vertical line.

A clear drop in the frequency of cases is visible beyond a distance of 50 miles from the city center of Washington D.C., the dashed vertical line. Additionally, only a few reviewers (2,088) are located within a distance of 50 to 100 miles to the center, compared with 28,261 reviewers located within a distance of 0 to 50 miles. This argument is used to separate local reviews (28,261) from non-local ones (72,570) by drawing a 50 mile radius around the center of Washington D.C. Reviewers were classified as locals if their location lies within 50 miles of the restaurant they reviewed and otherwise as visitors. The number of local/non-local reviews for each star rating category is summarized as follows (for the remainder of this paper, the values for locals are listed first, visitors second): one star: 985/1,633, two stars: 1,592/2,983, three stars: 4,188/9,020, four stars: 10,281/25,860 and five stars: 11,215/33,074. The reviewers' star ratings follow the typical J-shaped distribution toward more positive evaluations. As the smallest number of reviews over all cross-tabulated combinations (ten) was 985, this number of reviews was chosen randomly from the reviews for each combination to ensure a balanced proportion of the overall star rating categories for locals as well as visitors. This proportionate stratification sampling technique avoids distortions based on unbalanced star rating strata when later handed over to the linear regression model and allows for a direct comparison of locals versus visitors. Overall, $985 \times 10 = 9{,}850$ reviews entered the final analysis. The average number of terms per review was 52.55 with a total word count of 517,605 over all reviews that underwent the semantic analysis. In line with other authors (Bradley *et al.*, 2015; Zhao *et al.*, 2019), there is a visible tendency that the word count of negative reviews is longer compared with positive ones. The average word count for each star rating is summarized as follows: for locals/visitors: one star: 55.46/54.99, two stars: 55.29/55.61, three stars: 50.97/52.42, four stars: 50.62/49.98 and five stars: 55.77/49.37.

Several other variables were collected to provide an overview on reviewer characteristics: the number of reviews by each reviewer, the number of reviews by each reviewer that were rated with a "thumbs up" by other users to express its helpfulness and the review's character length. These items show significant differences between locals and visitors derived from non-parametric Mann–Whitney U-tests. Locals posted more reviews in general (92.13/69.99; $p = 0.006$) as well as more helpful reviews (48.12/40.27; $p < 0.001$). Furthermore, locals' reviews were longer (291.1/287.90; $p < 0.001$) even if just by 2.2 characters on average.

4.2 Validation of data-driven sentiment evaluations

For validation purposes, human-generated star ratings on TripAdvisor, measured on a five-point Likert-scale, were compared with machine-driven sentiment polarities, measured on a three-point Likert-scale. Both variables have their neutral position in the middle of the scale: a value of three for the human coded evaluations and a value of zero for the machine-driven evaluations. Therefore, four- and five-star TripAdvisor ratings should match with a positive sentiment polarity of 1, while star ratings of one and two should match with a -1 polarity. Table 2 cross-tabulates the TripAdvisor star ratings and the automatically coded polarities. According to this logic, the sum of the correctly classified reviews (12.2% + 10.2% + 3.7% + 18.6% + 16.4%) of all the 9,850 reviews is 61.17%. This shows that the machine-driven approach is able to tag the review content appropriately for classification and is, therefore, able to detect the correct polarities.

4.3 Relative overall and aspect-based sentiment polarities

Table 3 illustrates the reviewers' relative rating frequencies of the domain-specific aspect-based sentiment polarities of the 14 factors for locals and visitors. Concerning single factors, food was mentioned most often in a non-neutral way, with valenced expressions by 77.0% and 76.8% of reviewers (for locals and visitors, respectively). The sentiment was positive in 32.8% and 34.9% of cases and negative in 44.2% and 41.9% of cases. Of all the factors assessed, food is the most emotional factor and shows the most variation in valence. Therefore, food is identified as a critical factor when it comes to restaurant evaluations by both locals and visitors. A non-parametric Mann–Whitney U-test revealed that visitors evaluate food significantly more positively than do locals.

The second most frequently mentioned aspect was staff, for which a greater share of comments were positive (23.0% and 25.3%) than negative (20.3% and 22.1%), although the difference between locals and visitors was not significant. Facilities, reservations, cleanliness, desserts, quietness and payment evoked positive or negative emotions in less than 5% of cases for both locals and visitors and are mostly discussed in a neutral way, if at all. The strong dominance of the neutral position, also resulting from guests failing to

Table 2. Cross-tabulated data-driven sentiment polarities versus reviewers' star ratings

	TripAdvisor star rating					
	1	2	3	4	5	Total
Sentiment polarity						
−1						
Count	1,201	1,003	589	57	234	3,084
% of total	12.2%	10.2%	6.0%	0.6%	2.4%	31.3%
0						
Count	324	279	369	76	121	1,169
% of total	3.3%	2.8%	3.7%	0.8%	1.2%	11.9%
1						
Count	443	690	1,011	1,836	1,616	5,596
% of total	4.5%	7.0%	10.3%	18.6%	16.4%	56.8%

Table 3. Relative domain-specific aspect-based sentiment polarity percentages: locals versus visitors

Locals/Visitors	Positive (%)	Neutral (%)	Negative (%)	Sign
Drinks	7.8/10.7	79.0/76.6	13.1/12.7	< 0.001***
Facilities	0.5/0.7	97.9/98.5	1.5/0.8	0.002**
Food	32.8/34.9	23.0/23.2	44.2/41.9	0.013*
Busyness	7.6/10.0	87.1/84.0	5.3/6.1	0.031*
Menu	5.5/5.8	82.3/83.5	12.2/10.7	0.041*
Reservations	3.7/3.5	93.2/92.5	3.1/4.0	0.055 n.s.
Cleanliness	2.5/3.2	96.7/95.8	0.8/1.0	0.125 n.s.
Desserts	1.1/1.5	95.0/94.8	3.9/3.7	0.195 n.s.
Location	4.5/4.2	85.3/87.0	10.1/8.8	0.199 n.s.
Quietness	2.5/2.4	94.9/94.8	2.6/2.8	0.535 n.s.
Payment	1.0/1.1	98.8/98.7	0.2/0.2	0.584 n.s.
Ambience	2.2/2.0	87.6/88.1	10.2/9.9	0.836 n.s.
Value	8.6/9.2	82.2/80.6	9.2/10.2	0.619 n.s.
Staff	23.0/25.3	56.8/52.6	20.3/22.1	0.732 n.s.

Notes: Significance marked with *, ** and *** at α-levels of 5%, 1% and 0.1%

mention these factors in their reviews, led to insignificant differences between locals and visitors for all these factors, except facilities.

In general, all service quality aspects showing significant differences between the two groups were evaluated significantly more positively by visitors. It may be inferred that the expectation levels of locals are higher than those of visitors. These results clearly confirm *H2*, which states that there is a difference between locals and visitors regarding the valence of reviews discussing different restaurant factors.

4.4 Restaurant service aspect impacts on the overall evaluation

Figure 2 presents significance values of the linear regression models for both groups – locals and visitors – and visually summarizes the results. The overall star rating of the restaurant, as evaluated by the reviewer, is the dependent variable. The 14 restaurant service quality aspects were split into two dummy-coded items, one covering solely positive effects and one solely negative effects. The resulting 28 predictors were coded in the following way: positive items were assigned a value of one if the aspect-based sentiment was positive and a value of zero if it was neutral or negative. On the other hand, negative items got a value of one if the aspect-based sentiment was negative and a value of zero if it was neutral or positive. Both overall models are significant ($p < 0.001$), and the restaurant service aspects are able to explain 42.2% and 42.5% of the variance of the overall star ratings (adjusted R^2).

The most outstanding aspect is food, which shows the highest positive and negative impact for both groups. This again signals the crucial effect of food on sentiment toward the overall perception of the restaurant visit. One can also see that, for locals, the unstandardized estimated impact of positive reviews (0.691) is higher than that of negative reviews (−0.571) but that for visitors the situation is the other way around, with 0.515 and −0.717, respectively. This reversal of the strength of impact of positive and negative sentiment between the two groups is also observed for another item, namely drinks: 0.227 and −0.210 for locals and 0.132 and −0.287 for visitors.

Further differences between the two groups can be observed for location, payment and menu. For visitors, negative sentiment regarding these factors confers a significant impact on the overall star rating, but the same is not true for locals, for whom the expected level of quality regarding these items appears to be fulfilled. Contrary to this, positive sentiment for the factors of menu, ambience and busyness significantly impact on the overall star rating for locals but not for visitors. These items can have a positive impact on the overall star rating of locals if expectations are exceeded.

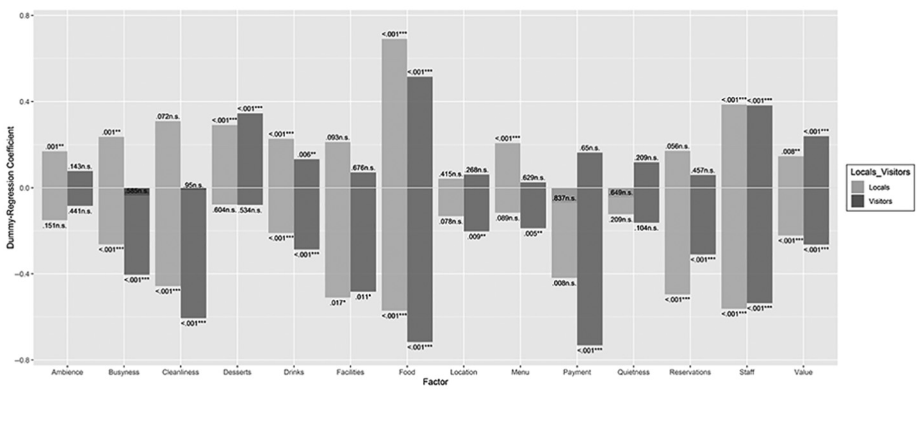

Figure 2.
Linear regression models – locals and visitors

These results verify that there is a difference between locals and visitors regarding positive impacts (*H3*) and negative impacts (*H4*) of restaurant factors mentioned in online reviews on the overall restaurant rating. Food shows the greatest impact on the overall evaluation for both groups, locals and visitors (*H1*). Thus, *H1* has to be rejected, although significant differences between the two groups were detected in terms of its evaluation (*H2*), as visitors review food significantly more positively than do locals.

5. Conclusions

Restaurant review platforms are popular with visitors as well as locals for selecting restaurants. Researchers have found that the importance of various service aspects is highly event-related; for example, price plays a less significant role in the context of an intimate dinner than in the context of a family dinner (June and Smith, 1987). Thus, consumers rate their overall restaurant experience according to their main reasons for dining-out. Based on this rationale, we argue that visitation motives differ between locals and visitors, and therefore, their restaurant evaluations emphasize different factors. Our literature review shows that no prior research has considered the importance of the different restaurant factors separately for these two groups of guests.

Thus, this study identifies the pivotal aspects of restaurant visits for different customer segments: locals and visitors. The results clearly show that there are differences between these two groups of restaurant guests in terms of restaurant characteristic evaluations or aspect importance for the overall restaurant evaluation on OTA platforms. The findings of this study indicate that food was the most frequently mentioned aspect in both positive and negative reviews for both groups of reviewers. Food also shows the strongest impact on the overall restaurant evaluation, whereby this impact is stronger for locals on the positive side and for visitors on the negative side. This result confirms previous findings in the literature, which state that food is the most important factor influencing the restaurant evaluation in online reviews (Gan *et al.*, 2017; Pantelidis, 2010; Zhang *et al.*, 2014), although previous studies have not been able to confirm this for the visitor segment. Thus, regarding the food aspect, new findings from the present study show that:

- there are more negative reviews than positive or neutral ones; and
- the polarity of these reviews is more balanced in the reviews of visitors.

Thus, visitors evaluate the food aspect significantly better than locals do, yet the impact of these positive evaluations on the overall restaurant rating is smaller compared to locals. One reason for this result could be a general lack of experience and opportunities for visitors to compare the different options available, leading visitors to be more easily satisfied than locals. This explanation notwithstanding, the finding that food has a greater positive impact on overall ratings for locals than for visitors requires further investigation. To provide more detailed insights on this issue in the future, one should take a closer look at the food criterion, as it is a very general term that can cover many different aspects. For example, food quality is mentioned as an important criterion in many studies, yet food also involves such issues as taste, presentation, textures and size of the portions (Erkmen, 2019).

No differences were detected between the two customer segments for the importance of the staff aspect, which is the second most important aspect for both groups and shows a predominantly negative contribution to the overall restaurant evaluation. For this aspect, results show more positive ratings (23.0% and 25.3%) than negative ones (20.3% and 22.1%) for both groups. Again, this result largely confirms the findings of previous studies, as the service aspect was among the top three most important factors in the evaluation of restaurants according to the literature review (Table 1).

Further differences between the two groups regarding the overall restaurant star rating can be observed for location, payment, menu, ambience and busyness. Location, payment and menu have a significant negative impact on the overall star rating for visitors but not for locals, while there was no difference regarding the valence of the reviews between these two groups toward the items location and payment. Conversely, menu, ambience and busyness have significant positive impacts for locals but not for visitors. Surprisingly, and contrary to previous findings, ambience does not appear to matter much to visitors, while for locals, it exclusively leads to positive overall ratings. Thus, visitors' expectations concerning the ambience, unlike those of locals, are not exceeded. However, as with food, there are also many different factors that contribute to the restaurant ambience including décor, noise level, temperature, lighting, color and music. Thus, this calls for further investigation to examine and describe this aspect in greater detail.

Furthermore, facilities, menu and busyness were evaluated more positively by visitors than locals. Regarding the valence of the reviews, greater differences were found between locals and visitors for evaluations of busyness. This result is somewhat surprising when one considers crowded tourist restaurants. Apparently, a certain amount of activity is preferred by both groups, whereby the visitors perceive this busyness a little more positively. However, concerning this factor, only negative online reviews about the busyness exhibit an impact on overall restaurant evaluation for visitors, while for locals, there is an influence from both directions. These findings suggest that the expectation level of visitors is likely to be higher than those of locals. For facilities and menu, the difference between the two groups in terms positive versus negative reviews is marginal.

6. Practical implications

From a managerial point of view, these findings can help restaurant managers to better understand their customers' needs. An understanding of customer dining experiences is critical for restaurants to develop effective marketing strategies to encourage customers to patronize their restaurants. Furthermore, managers must decide which restaurant aspects should receive the most attention and how investments can best be directed to ensure that customers are satisfied and subsequently communicate this through online marketing communications. The results of this study clearly show that different customer segments (locals and visitors) focus on different factors when evaluating restaurants in online reviews. Thus, restaurants managers have to be aware of the visitation motives of their guests, and restaurant marketers may benefit by developing a motivation-based classification system for their guests. Accordingly, communications can emphasize the attributes that are most important for the corresponding motivation-based target group.

In line with prior literature, the findings reveal that food is the most important determinant in consumers' dining evaluations and evokes the most pronounced feelings for both locals and visitors. Thus, an important managerial implication is that food quality, for example, the taste and the presentation of the food, should always constitute an important component of marketing activities, regardless which customer segment is addressed. However, the findings also reveal interesting points of differences regarding the food factor between locals and visitors which should be taken into account by restaurant managers: in contrast to locals who are impacted more strongly by positive experiences, visitors are impacted more strongly by negative experiences. This leads to the conclusion that visitors have a certain idea about the quality of food, which can have a strong negative impact on the overall dining experience when these expectations are not fulfilled. Following this notion, destination marketers may emphasize the cultural aspects of local cuisine in promoting the destination but, at the same time, should convey a realistic picture of local tastes so as not to raise expectations too high.

It is not only the aspect of food which is highly relevant for destination management organizations (DMOs). Destinations need to understand the relative importance and performance of all dining attributes and manage these attributes accordingly. The results of this study further suggest that visitors pay more attention to contextual factors than locals do. Especially payment options and the location of a restaurant both contribute negatively to the overall assessment of visitors compared with locals. From these results, it can be concluded that DMOs have to ensure that local restaurants take the visitors' expectations seriously and, for example, offer multiple payment options. Regarding the restaurant location, further investigation is needed to identify the reasons why the location has a negative impact on the overall evaluation for visitors but not for locals. This result might be explained by the familiarity of locals with their living area, while visitors struggle to find places that are not centrally located. To counteract this, restaurants should ensure that they offer comprehensive directions on their websites or in tourist guides.

For busyness, the findings reveal that although this factor is mentioned more often by visitors than by locals, both in negative and positive terms, its impact on the overall evaluation is exclusively negative for visitors, whereas the impact can also be positive for locals. Therefore, restaurant managers would be advised to find strategies to spread the rush at peak times, for example, by offering happy hours during off-peak hours to avoid negative reviews from both target groups.

Further, the results show that staff (in terms of service quality) is an important factor for both groups, and they do not differ in this respect. This leads to the conclusion that staff is important for all restaurants, regardless whether they are located in tourist areas or not. In comparison, there are indeed differences concerning the valence of reviews between locals and visitors for the menu factor as well as for facilities. Both factors are rated significantly better by visitors, which leads to the assumption that restaurants that intend to attract locals should perform better in these areas. Furthermore, these factors contribute to the overall star ratings differently between these two customer segments. For visitors, the menu has an exclusively negative impact, whereas for locals, this factor has a solely positive impact. Locals evaluate the menu from a more comparative perspective with specific expectations concerning the range of food and beverages offered. As visitors lack a comprehensive overview of the local gastronomy, the impact of the menu on the overall star rating seems to be mainly driven by the culinary experience.

To conclude, it would be advisable for DMOs and restaurant managers to view gastronomic experiences as a holistic product also covering factors other than the food.

Implications for restaurant managers can also be derived from the methodological approach of this study. Although reviews play a crucial role in the decision-making process of travelers, the massive amount of data involved place a large burden on service managers. The automatic text-mining technique applied here is of great practical utility for the systematic monitoring of online reviews.

7. Theoretical implications

The uniqueness of the present study from an academic perspective is the geo-location-based method used to differentiate between two restaurant customer segments in online reviews, namely locals and visitors. This should also inform other related disciplines where the need to distinguish between the two is of relevance. The thorough literature review which forms the basis of this paper demonstrates that it is important to analyze different restaurant customer segments separately: an issue that has so far received too little attention in tourism literature. Hence, in addition to common a posteriori determined classifications and a priori known segments based on socio-demographic aspects, the geographical element must not be neglected, as shown in this investigation.

The second contribution relates to the application of domain-specific aspect-based sentiment analysis to understand consumers' sentiments in online restaurant reviews. From a methodological perspective, the used approach, the AYLIEN text analysis API, an extension of the RapidMiner Studio platform, proved to be a valid and efficient replacement to the task of manual coding.

Finally, the dummy regression approach separates positive from negative impacts and reveals coefficients for both sides. Each factor is assumed to be able to provoke positive as well as negative perceptions in parallel. For instance, the taste of food may be nice, but the presentation of the food may be bad. Past studies dealing with online reviews have not taken this separation into account and have focused only on the dominant impact. If neither positive nor negative service outcomes are prevalent or both cancel each other out, then the resulting conclusion has traditionally been that this factor has no impact and no managerial reaction is necessary. But this does not have to be true, and neutralizing negative perceptions can result in the dominance of positive ones. Dummy coding of extreme attribute evaluations facilitates investigation of such phenomena.

8. Limitations and future research

As regards the limitations of the study, it must be recognized that the analysis was restricted to a probability sample extracted from 100,831 online reviews of restaurants located in the city of Washington D.C. However, geographical and cultural characteristics might play their role. Effect size comparisons between different regions are likely to reveal varying impacts of restaurant service features on the overall restaurant evaluation because of cultural differences. For example, online consumer product reviews derived from Amazon show that American consumers focus more on the usability features of products compared with Chinese consumers, who put a focus on aesthetics of the products (Wang *et al.*, 2015). This might be true for restaurant service features as well. Thus, future studies should examine cultural differences by focusing on different geographic areas, as well as the specification of the geographical distance separating locals from visitors.

Furthermore, the data examined herein include different types of restaurants. However, different conclusions might be derived for different types of restaurants. For example, the requirements for a fast food restaurant are quite different from those of higher category restaurants. Thus, it would be interesting to compare reviews of different types of restaurants.

A further limitation, applicable to all studies that work with online reviews, is the generalization of the results, as not all customers leave comments on online review websites. This leads to a sampling problem because customers posting online reviews might differ in many aspects from customers avoiding online reviews. While those that leave reviews may be considered especially important because of their ability to influence a wide audience, their experiences should not be automatically regarded as representative of diners in general.

Additionally, the study assumes that all reviews analyzed are reflective of honest consumer opinions. This might not be true, as fake reviews are not uncommon and it is likely that manipulations were included in the present sample.

Finally, the sentiment detection procedure has an inherent limitation, as it was restricted to 14 pre-defined factors. In the regression model on the overall restaurant star rating, the adjusted R^2 reached a value of 42.2% (locals) and 42.5% (visitors). A complete picture of one's opinion is only possible if all factors are determined in an explorative way and evaluated subsequently. Nevertheless, the 14 restaurant service aspects capture the most important ones previously identified in the literature. Future studies might use data-driven approaches to derive an even longer list of attributes by mining online reviews.

References

Aicher, J., Asiimwe, F., Batchuluun, B., Hauschild, M., Zöhrer, M., Egger, R. (2016), "Online hotel reviews: Rating symbols or text . . . text or rating symbols? That is the question!", In Inversini, A. and Schegg, R. (Eds), *Information and Communication Technologies in Tourism 2016*, Springer, Cham, pp. 369-382.

Alaei, A.R., Becken, S. and Stantic, B. (2017), "Sentiment analysis in tourism: Capitalizing on big data", *Journal of Travel Research*, Vol. 58 No. 2, pp. 175-191.

Berezina, K., Bilgihan, A., Cobanoglu, C. and Okumus, F. (2016), "Understanding satisfied and dissatisfied hotel customers: text mining of online hotel reviews", *Journal of Hospitality Marketing and Management*, Vol. 25 No. 1, pp. 1-24.

Björk, P. and Kauppinen-Räisänen, H. (2016), "Local food: a source for destination attraction", *International Journal of Contemporary Hospitality Management*, Vol. 28 No. 1, pp. 177-194.

Bradley, G.L., Sparks, B.A. and Weber, K. (2015), "The stress of anonymous online reviews: a conceptual model and research agenda", *International Journal of Contemporary Hospitality Management*, Vol. 27 No. 5, pp. 739-755.

Chang, J., Khan, M.A. and Tsai, C.T.S. (2012), "Dining occasions, service failures and customer and customer complaint behaviours: an empirical assessment", *International Journal of Tourism Research*, Vol. 14 No. 6, pp. 601-615.

Chang, R.C.Y., Kivela, J. and Mak, A.H.N. (2011), "Attributes that influence the evaluation of travel dining experience: when east meets west", *Tourism Management*, Vol. 32 No. 2, pp. 307-316.

Churchill, R. (2019), "Washington D.C. TripAdvisor restaurant data [data file]".

East, R., Hammond, K. and Lomax, W. (2008), "Measuring the impact of positive and negative word of mouth on brand purchase probability", *International Journal of Research in Marketing*, Vol. 25 No. 3, pp. 215-224.

Erkmen, E. (2019), "Managing restaurant attributes for destination satisfaction: what goes beyond food?", *Administrative Sciences*, Vol. 9 No. 1, pp. 19-30.

Fields, K. (2002), "Demand for the gastronomy tourism product: motivational factors", in Hjalager, A.-M. and Richards, G. (Ed.s), *Tourism and Gastronomy*, Routledge, London, pp. 36-50.

Gan, Q., Ferns, B.H., Yu, Y. and Jin, L. (2017), "A text mining and multidimensional sentiment analysis of online restaurant reviews", *Journal of Quality Assurance in Hospitality and Tourism*, Vol. 18 No. 4, pp. 465-492.

Gavilan, D., Avello, M. and Martinez-Navarro, G. (2018), "The influence of online ratings and reviews on hotel booking consideration", *Tourism Management*, Vol. 66, pp. 53-61.

Getz, D., Robinson, R., Andersson, T. and Vujicic, S. (2014), *Foodies and Food Tourism*, Goodfellow Publishers Limited, Oxford.

Gottschalk, S.A. and Mafael, A. (2017), "Cutting through the online review jungle – investigating selective eWOM processing", *Journal of Interactive Marketing*, Vol. 37, pp. 89-104.

Guo, Y., Barnes, S.J. and Jia, Q. (2017), "Mining meaning from online ratings and reviews: tourist satisfaction analysis using latent dirichlet allocation", *Tourism Management*, Vol. 59, pp. 467-483.

Gupta, S., McLaughlin, E. and Gomez, M. (2007), "Guest satisfaction and restaurant performance", *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 48 No. 3, pp. 284-298.

Hyun, S.S. (2010), "Predictors of relationship quality and loyalty in the chain restaurant industry", *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 51 No. 2, pp. 251-267.

Jacobsen, J.K.S. and Haukeland, J.V. (2002), "A lunch with a view: Motor tourists' choices and assessments of eating-places", *Scandinavian Journal of Hospitality and Tourism*, Vol. 2 No. 1, pp. 4-16.

Jeong, E.H. and Jang, S.C. (2011), "Restaurant experiences triggering positive electronic word-of-mouth (eWOM) motivations", *International Journal of Hospitality Management*, Vol. 30 No. 2, pp. 356-366.

June, L.P. and Smith, S.L. (1987), "Service attributes and situational effects on customer preferences for restaurant dining", *Journal of Travel Research*, Vol. 26 No. 2, pp. 20-27.

King, R.A., Racherla, P. and Bush, V.D. (2014), "What We know and don't know about online word-of-Mouth: a review and synthesis of the literature", *Journal of Interactive Marketing*, Vol. 28 No. 3, pp. 167-183.

Kivela, J. and Crotts, J.C. (2006), "Tourism and gastronomy: gastronomy's influence on how tourists experience a destination", *Journal of Hospitality and Tourism Research*, Vol. 30 No. 3, pp. 354-377.

Li, H., Zhang, Z., Meng, F. and Zhang, Z. (2019), "When you write review' matters: the interactive effect of prior online reviews and review temporal distance on consumers' restaurant evaluation", *International Journal of Contemporary Hospitality Management*, Vol. 31 No. 3, pp. 1273-1291.

Lin, Y.C., Pearson, T.E. and Cai, L.A. (2011), "Food as a form of destination identity: a tourism destination brand perspective", *Tourism and Hospitality Research*, Vol. 11 No. 1, pp. 30-48.

Liu, B. (2012), "Sentiment analysis and opinion mining", *Synthesis Lectures on Human Language Technologies*, Vol. 5 No. 1, pp. 1-167.

Liu, Y. and Jang, S.S. (2009), "Perceptions of Chinese restaurants in the US: what affects customer satisfaction and behavioral intentions?", *International Journal of Hospitality Management*, Vol. 28 No. 3, pp. 338-348.

Lu, X., Ba, S., Huang, L. and Feng, Y. (2013), "Promotional marketing or word-of-mouth? Evidence from online restaurant reviews", *Information Systems Research*, Vol. 24 No. 3, pp. 596-612.

Medeiros, C.O. and Salay, E. (2013), "A review of food service selection factors important to the consumer", *Food and Public Health*, Vol. 3 No. 4, pp. 176-190.

Mellinas, J.P. and Reino, S. (2018), "Word of mouth, the importance of reviews and ratings in tourism marketing", in Camilleri, M.A. (Ed.), *IGI Global 2018: Strategic Perspectives in Destination Marketing*, pp. 143-173.

Namkung, Y. and Jang, S. (2008), "Are highly satisfied restaurant customers really different? A quality perception perspective", *International Journal of Contemporary Hospitality Management*, Vol. 20 No. 2, pp. 142-155.

Nield, K., Kozak, M. and LeGrys, G. (2000), "The role of food service in tourist satisfaction", *International Journal of Hospitality Management*, Vol. 19 No. 4, pp. 375-384.

Pang, B. and Lee, L. (2008), "Opinion mining and sentiment analysis", *Foundations and Trends® in Information Retrieval*, Vol. 2 Nos 1/2, pp. 1-135.

Pantelidis, I.S. (2010), "Electronic meal experience: a content analysis of online restaurant comments", *Cornell Hospitality Quarterly*, Vol. 51 No. 4, pp. 483-491.

Parsa, H.G., Gregory, A., Self, J.T. and Dutta, K. (2012), "Consumer behavior in restaurants: assessing the importance of restaurant attributes in consumer patronage and willingness to pay", *Journal of Services Research*, Vol. 12 No. 2, pp. 29-56.

Pizam, A., Jeong, G.H., Reichel, A., van Boemmel, H., Lusson, J.M., Steynberg, L.O., State-Costache, O., Volo, S., Kroesbacher, C., Kucerova, J. and Montmany, N. (2004), "The relationship between risk-taking, sensation-seeking, and the tourist behavior of young adults: a cross-cultural study", *Journal of Travel Research*, Vol. 42 No. 3, pp. 251-260.

Ponnam, A. and Balaji, M.S. (2014), "Matching visitation-motives and restaurant attributes in casual dining restaurants", *International Journal of Hospitality Management*, Vol. 37, pp. 47-57.

Ruder, S. and Plank, B. (2018), "Strong baselines for neural semi-supervised learning under domain shift", *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, Association for Computational Linguistics*, pp. 1-11.

Ruder, S., Ghaffari, P. and Breslin, J.G. (2016a), "A hierarchical model of reviews for aspect-based sentiment analysis", *in Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, The Association of Computational Linguistics*, *Austin*, pp. 999-1005.

Ruder, S., Ghaffari, P. and Breslin, J.G. (2016b), "Deep learning for multilingual aspect-based sentiment analysis", in *Proceedings of the 10th International Workshop on Semantic Evaluation (SemEval-2016)*, *Association of Computational Linguistics*, pp. 330-336.

Ryu, K. and Han, H. (2010), "Influence of the quality of food, service, and physical environment on customer satisfaction and behavioral intention in quick-casual restaurants: moderating role of perceived price", *Journal of Hospitality and Tourism Research*, Vol. 34 No. 3, pp. 310-329.

Schuckert, M., Liu, X. and Law, R. (2015), "Hospitality and tourism online reviews: recent trends and future directions", *Journal of Travel and Tourism Marketing*, Vol. 32 No. 5, pp. 608-621.

Sparks, B.A., Wildman, K.L. and Bowen, J.T. (2001), "Restaurants as a contributor to tourist destination attractiveness", *Australian Journal of Hospitality Management*, Vol. 8 No. 2, pp. 17-30.

Stone, M.J., Migacz, S. and Wolf, E. (2019), "Beyond the journey: the lasting impact of culinary tourism activities", *Current Issues in Tourism*, Vol. 22 No. 2, pp. 147-152.

Vu, H.Q., Li, G., Law, R. and Zhang, Y. (2019), "Exploring tourist dining preferences based on restaurant reviews", *Journal of Travel Research*, Vol. 58 No. 1, pp. 149-167.

Wall, E.A. and Berry, L.L. (2007), "The combined effects of the physical environment and employee behavior on customer perception of restaurant service quality", *Cornell Hotel and Restaurant Administration Quarterly*, Vol. 48 No. 1, pp. 59-69.

Wang, Y., Wang, Z., Zhang, D. and Zhang, R. (2015), "Discovering cultural differences in online consumer product reviews", *Journal of Electronic Commerce Research*, Vol. 20 No. 3, pp. 169-183.

White, R. and Buscher, G. (2012), "Characterizing local interests and local knowledge", in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 1607-1610.

Wilkinson, P.F. (2016), "Foodies and food tourism", *Annals of Leisure Research*, Vol. 19 No. 1, pp. 139-141.

Xiang, Z., Du, Q., Ma, Y. and Fan, W. (2017), "A comparative analysis of major online review platforms: implications for social media analytics in hospitality and tourism", *Tourism Management*, Vol. 58, pp. 51-65.

Yan, X., Wang, J. and Chau, M. (2015), "Customer revisit intention to restaurants: evidence from online reviews", *Information Systems Frontiers*, Vol. 17 No. 3, pp. 645-657.

Zhang, Z., Zhang, Z. and Law, R. (2014), "Positive and negative word of mouth about restaurants: exploring the asymmetric impact of the performance of attributes", *Asia Pacific Journal of Tourism Research*, Vol. 19 No. 2, pp. 162-180.

Zhang, Z., Liang, S., Li, H. and Zhang, Z. (2019), "Booking now or later: do online peer reviews matter?", *International Journal of Hospitality Management*, Vol. 77, pp. 147-158.

Zhao, Y., Xu, X. and Wang, M. (2019), "Predicting overall customer satisfaction: big data evidence from hotel online textual reviews", *International Journal of Hospitality Management*, Vol. 76, pp. 111-121.

Zhao, X., Wang, L., Guo, X. and Law, R. (2015), "The influence of online reviews to online hotel booking intentions", *International Journal of Contemporary Hospitality Management*, Vol. 27 No. 6, pp. 1343-1364.

Appendix

	Estimate	SE	t-value	P(>t)	Significance
Intercept	2.922/3.174	0.038/0.037	77.233/85.121	< 0.001/< 0.001	***/***
Food					
+	0.691/0.515	0.042/0.043	16.505/12.095	< 0.001/< 0.001	***/***
−	−0.571/−0.717	0.043/0.043	−13.140/−16.803	< 0.001/< 0.001	***/***
Staff					
+	0.386/0.382	0.041/0.041	9.336/9.295	< 0.001/< 0.001	***/***
−	−0.562/−0.536	0.041/0.040	−13.558/−13.348	< 0.001/< 0.001	***/***
Busyness					
+	0.236/−0.036	0.070/0.066	3.347/−0.547	0.001/0.585	**/n.s.
−	−0.263/−0.404	0.061/0.054	−4.303/−7.540	< 0.001/< 0.001	***/***
Cleanliness					
+	0.309/−0.010	0.171/0.158	1.802/−0.062	0.072/0.950	n.s./n.s.
−	−0.457/−0.606	0.100/0.088	−4.569/−6.878	< 0.001/< 0.001	***/***
Reservations					
+	0.171/0.059	0.089/0.079	1.910/0.744	0.056/0.457	n.s./n.s.
−	−0.496/−0.310	0.084/0.085	−5.914/−3.651	< 0.001/< 0.001	***/***
Drinks					
+	0.227/0.132	0.047/0.048	4.814/2.749	< 0.001/0.006	***/**
−	−0.210/−0.287	0.060/0.052	−3.496/−5.488	< 0.001/< 0.001	***/***
Payment					
+	−0.070/0.163	0.341/0.359	−0.205/0.454	0.837/0.650	n.s./n.s.
−	−0.419/−0.732	0.158/0.149	−2.660/−4.906	0.008/< 0.001	*n*.s./***
Value					
+	0.146/0.239	0.055/0.053	2.674/4.513	0.008/< 0.001	**/***
−	−0.222/−0.264	0.057/0.056	−3.919/−4.749	< 0.001/< 0.001	***/***
Menu					
+	0.207/0.025	0.048/0.051	4.276/0.484	< 0.001/0.629	***/n.s.
−	−0.116/−0.188	0.068/0.066	−1.700/−2.832	0.089/0.005	n.s./**
Desserts					
+	0.291/0.345	0.080/0.082	3.631/4.205	< 0.001/< 0.001	***/***
−	−0.078/−0.080	0.150/0.128	−0.519/−0.622	0.604/0.534	n.s./n.s.
Ambience					
+	0.169/0.077	0.052/0.053	3.254/1.466	0.001/0.143	**/n.s.
−	−0.151/−0.084	0.105/0.110	−1.437/−0.771	0.151/0.441	n.s./n.s.
Facilities					
+	0.212/0.071	0.126/0.169	1.682/0.417	0.093/0.676	n.s./n.s.
−	−0.510/−0.483	0.213/0.189	−2.394/−2.553	0.017/0.011	*/*

(*continued*)

Table A1. Linear regression model: locals versus visitors

Table A1.

	Estimate	SE	t-value	P(>t)	Significance
Quietness					
+	−0.044/0.118	0.097/0.094	−0.455/1.255	0.649/0.209	n.s./n.s.
−	−0.123/−0.162	0.098/0.100	−1.256/−1.627	0.209/0.104	n.s./n.s.
Location					
+	0.042/0.061	0.052/0.055	0.815/1.109	0.415/0.268	n.s./n.s.
−	−0.132/−0.203	0.075/0.078	−1.763/−2.615	0.078/0.009	n.s./**

Notes: Significance marked with *, ** and *** at α-levels of 5%, 1% and 0.1%

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