A sentiment analysis of Michelin-starred restaurants

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Abstract

Purpose – With the growing popularity of social media, it has become common practice for consumers to write online reviews to share their opinion and experience as well as consider others' reviews to inform purchase decision-making. This study investigated how online review sentiments towards four key aspects (food, service, ambience and price) change after a restaurant is awarded a Michelin Star to shed light on how the award of a Michelin Star affects online reviews as well as what factors contribute to positive online restaurant reviews.

Design/methodology/approach – The authors conducted a sentiment analysis of online restaurant reviews on TripAdvisor. A total of 8,871 English-written reviews from 87 restaurants located in Europe were extracted using a web crawler developed by Beautiful Soup, and data were then processed using Semantria.

Findings – The study findings revealed that overall sentiments decreased after restaurants were awarded a Michelin Star, in which service sentiment was the most affected aspect, followed by food and ambience. Yet, price sentiment showed a prominent increase. This provides valuable insights for Michelin-starred restaurant operators and owners to create a unique and compelling gastronomic experience that triggers positive online reviews.

Practical implications – The results of this study argue that consumers tend to hold higher expectations for this type of upscale restaurants given its recognition and quality assurance, so they are more likely to have negative feelings when their expectations are disconfirmed. Therefore, restaurants should continuously improve their food and service while paying attention to small details such as ambience, through creativity and innovation. Also, high-end restaurants, especially Michelin-starred restaurants, usually have the edge in premium pricing, yet competitive pricing may backfire considering its perceived luxurious values.

Originality/value – This study analyzed changes in customer sentiments when a restaurant is awarded a Michelin Star through text analytics. Through the lens of online restaurant reviews, the study findings contribute to identifying aspects that are most or least affected by the award of a Michelin Star as well as highlight the role of ambience in customer satisfaction which might have been overlooked in previous studies.

Keywords Online restaurant reviews, TripAdvisor, Sentiment analysis, Text analytics, Michelin-starred restaurants

Paper type Research paper

Introduction

Consumers' decision-making is often influenced by peer recommendations (Libai *et al.*, 2010; Van Doorn *et al.*, 2010). Nowadays, with the increased use of Internet and social media platforms (Hennig-Thurau *et al.*, 2010), consumers do not just rely on their friends' opinions when making purchase decisions; they place their trust in a much wider group of people who have already used the product or service. Such behavior has increased the influence of online reviews on consumer decisions since they have become the new form of word-of-mouth, and customers tend to find them more reliable (Banerjee *et al.*, 2017). Accordingly, high rating

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and positive reviews on online social platforms or review platforms present some advantages for businesses to build online reputation and eventually influence sales (Banerjee *et al.*, 2017). Particularly, in the context of high-end restaurants, word-of-mouth and review ratings are considered important sources influencing one's decision-making (Harrington *et al.*, 2013). Alternatively, perhaps more traditional, the Michelin Guide is acknowledged as an authoritative reference for consumers who intend to dine at a fine-dining establishment.

With the aim of promoting road travel, the Michelin Guide started as a guide to provide motorists with information such as maps, petrol stations and accommodation. In 1926, the Guide began to award a single star for restaurant excellence, followed five years later by a rating system from zero to three stars (Michelin Guide, n.d.-a). Today, Michelin-starred restaurants are internationally recognized for culinary excellence, with restaurants usually experiencing a substantial increase in customers after being awarded a star (Chiang and Guo, 2021; Vargas-Sanchez and López-Guzmán, 2022). Accordingly, this type of high-end restaurants has attracted considerable scholarly attention.

Michelin-starred restaurants are often regarded as fine-dining establishments (Chiang and Guo, 2021), positioned in the high-end or luxury segment (Pacheco, 2018) and characterized as haute cuisine that is driven by excellence (Svejenova *et al.*, 2007). On a rating system from zero to three stars, Michelin stars are awarded to restaurants based on five criteria: "quality of the ingredients used, mastery of flavor and cooking techniques, the personality of the chef in his/her cuisine, value for money and consistency between visits," in which one star is given to restaurants with "high-quality cooking", two stars represents "excellent cooking", while three stars means "exceptional cooking" (Michelin Guide, n.d.-b).

Prior studies on Michelin-starred restaurants primarily adopted traditional approaches such as surveys and interviews to understand consumers' perceptions (Chiang and Guo, 2021; Liu *et al.*, 2022), decision process in high-end restaurant selection (Harrington *et al.*, 2013), drivers of fine-dining consumption (Kiatkawsin and Han, 2019), fine-dining customer satisfaction and loyalty formation (Kiatkawsin and Sutherland, 2020). In recent years, the prevalent use of online social media or review platforms in consumers' restaurant decision-making process has attracted hospitality and tourism scholars to move toward the adoption of analytical methods in their studies. For example, the performance of sentiment analysis to identify attributes that affect restaurant star ratings (Gan *et al.*, 2017), the analysis of TripAdvisor reviews on Michelin-starred restaurants to investigate the relationship between overall satisfaction and the four commonly accepted attributes that explain restaurant experience (food, service, ambience and price) (Pacheco, 2018), the use of online restaurant reviews and text analytics to provide insights into tourists' dining preferences (Vu *et al.*, 2019) and the adoption of the text mining approach to identify what drives customers to write explicit online reviews (Guerreiro and Rita, 2020). Nevertheless, studies that apply data-driven approaches like social media analytics in the context of Michelin-starred restaurants remain scarce. Concerning the benefits of Michelin stars for restaurants, such as increased reputation and sales, this study aims to investigate the changes in customer sentiments toward a restaurant before and after the award of a Michelin Star through sentiment analysis of online restaurant reviews.

In this study, we address three research questions: (1) Does the award of a Michelin Star influence customers' overall sentiment towards the restaurant? (2) What dimensions (food, service, price and ambiance) are most or least affected after a restaurant has obtained a Michelin Star? (3) What are the dimensions that impact the overall sentiment the most?

The remainder of this paper is organized as follows: section 2 reviews literature related to Michelin-starred restaurants, consumer dining experience, perceptions and attitudes toward Michelin-starred restaurants, natural language processing and sentiment analysis; section 3 presents the conceptualization and research hypotheses; section 4 introduces the methodology used in the analysis; finally, section 5 discusses the results, whereas section 6 provides theoretical and practical implications, identifies limitations and puts forward recommendations for future research.

Literature review

Online reviews

Electronic word-of-mouth (e-WOM) has attracted much attention from researchers and practitioners in the last decades given its significant influence on consumers' decision making and behaviors (Tsao and Hsieh, 2015). Litvin *et al.* (2008) defined it as "all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers", based on Westbrook's (1987) WOM definition.

One of the forms that e-WOM can take is online reviews, which can "be defined as peer-generated product evaluations posted on the company or third-party websites" (Mudambi and Schuff, 2010). Online reviews can be found on retail, restaurant, and hotel review platforms, such as TripAdvisor, Zomato, or Yelp. Amazon.com initiated the rating system in the late 1990s and since then, it has become a widely used tool for consumers to share their experiences and voice their opinions online (Bilgihan *et al.*, 2018). These can usually be composed of two components: a quantitative review (usually on a scale from 1 to 5 stars) and a qualitative review, i.e. a written comment.

Gretzel and Yoo (2008) found that other travelers' reviews increased confidence and reduced the risk of regretting a purchase. Given the intangible nature of services, consumers tend to rely on peer recommendations such as online reviews when selecting a restaurant (Hennig-Thurau *et al.*, 2010; Lee and Kim, 2020; Libai *et al.*, 2010; Meek *et al.*, 2021; Van Doorn *et al.*, 2010). Nowadays, consumers tend to consider online reviews when making a purchase decision. Banerjee *et al.* (2017) investigated what characteristics of reviewers affected their trustworthiness the most and proposed a model that can be used to predict reviewer's trustworthiness. There were also studies conducted to understand how online reviews affect sales. For example, Zhu and Zhang (2010) stated that previous studies were not conclusive regarding the effect of reviews on sales as the reviews studied applied to products that were sold solely online, rather than those sold offline. Even if we do not find a direct correlation between both, we can understand that online reviews have an influence on sales based on their trustworthiness and the amount of positive or negative reviews.

Consumer dining experience in Micheline-starred restaurants

Generally, dining experience may be divided into four aspects: food quality, service, ambience, and price fairness (Nakayama and Wan, 2019). Particularly, Berry *et al.* (2006) proposed that dining experience is a multidimensional concept that encompasses three major clues, including mechanic, humanic, and functional. Mechanic clues focus on the "what" that contributes to customers' cognitive perceptions and refer to the physical setting such as environment and ambience; humanic and functional clues focus on the "how" that contributes to customers' affective perceptions, in which the former is concerned with the service providers and the way they behave, while the latter is generated from food and services that are considered the core attributes of a restaurant (Berry *et al.*, 2006; Garg and Amelia, 2016). Different clues vary in importance in different contexts. In fine-dining, functional clues do not necessarily lead to success but are considered the basics for any high-end restaurant as fine-dining customers usually expect quality and unique experience beyond good food (Berry *et al.*, 2006), while functional clues are the tangible aspects that assist customers in evaluating their dining experience (Chua *et al.*, 2014). Humanic clues (i.e. staff's appearance and how the staff serves customers) play a vital role in influencing one's first impression of a fine dining restaurant, and accordingly customer satisfaction and loyalty (Amelia and Garg, 2016). Similarly, Alcoba *et al.* (2020)'s findings suggested that the experiential aspects, particularly treatment, are what customers value the most in a Michelin-starred restaurant. Also, Kiatkawsin and Sutherland (2020) indicated that dining experience in Michelin-starred restaurants is not only about food and beverage, but more importantly, luxury restaurant patrons particularly look for experiential quality such as interaction with the restaurant and service performance throughout the meal. Meanwhile, recent scholars suggested that a business model driven by innovation and creativity is crucial for the success of Michelin-starred restaurants because the core is to provide customers with unique gastronomic experiences (Madeira *et al.*, 2022; Vargas-Sanchez and López-Guzmán, 2022).

Consumer perceptions and attitudes towards Michelin-starred restaurants

Perception and attitude are two key determinants of consumers' purchase intention. Chiang and Guo (2021) found that consumers' perception of Michelin Guide positively affected their attitude towards Michelin-starred restaurants given its credibility and trustworthiness. Consumers often perceive Michelin-starred restaurants as prestige and luxury brands that offer unique and luxurious values, and therefore are willing to pay a higher price (Kiatkawsin and Han, 2019; Liu *et al.*, 2022). However, purchasing luxury services such as dining at a Michelin-starred restaurant is associated with relatively high levels of uncertainty given its intangible nature and premium price (Chen and Peng, 2018). Consequently, consumers' perceptions of luxury restaurants, such as perceived financial risk, may affect their purchase decision (Yang and Mattila, 2016). Nevertheless, consumers' perceived risk may reduce if they have sufficient information on the products and services offered by luxury restaurants, particularly through word-of-mouth, thus creating a positive perception (Chiang and Guo, 2021; Garg and Amelia, 2016).

Consumer attitude is a consumer's overall assessment of a product or service (Hwang and Ok, 2013). Understanding consumers' attitudes towards Michelin-starred restaurants is crucial as it will eventually influence one's purchase intention (Chiang and Guo, 2021). Voss *et al.* (2003) proposed that consumer attitude is a complex concept but may be generally measured by two dimensions, namely hedonic (e.g. fun, excitement, and surprise) and utilitarian (e.g. convenience, value for money, and service quality). Hwang and Ok (2013)'s findings suggested that fine-dining patrons placed greater emphasis on the hedonic aspect than utilitarian because they usually seek excitement or unique experience rather than simply satisfying hunger; meanwhile, utilitarian attitude may be enhanced through service excellence in a fine-dining setting. In addition, consumers with different needs might hold different attitudes towards Michelin-starred restaurants. For example, Lee and Hwang (2011) found that consumers whose luxury consumption is motivated by materialism that signifies high status and possession or by hedonism that emphasizes emotional pleasure tend to hold a positive attitude towards luxury restaurants, while consumers who desire to feel different from other people by possessing unusual or unique items hold negative attitudes towards luxury restaurants.

Natural language processing and sentiment analysis

Natural language processing (NLP) is a branch of artificial intelligence that is capable of reading and understanding a large amount of text generated by humans, such as reviews on social media platforms, and converting it into structured data for analysis purposes (Patel and Patel, 2021). As posting online reviews has become a common practice for consumers to share their opinions and experiences about particular products or services (Rouliez *et al.*, 2019), and the majority of travelers tend to rely on online reviews to inform travel decision making (Hu and Yang, 2021), online review platforms have become valuable sources for marketers to obtain firsthand information about their customers' feedback and needs. Accordingly, the application of NLP has gained popularity in the hospitality and tourism domain (Vargas-Calderón *et al.*, 2021). In particular, sentiment analysis is one of the most significant applications of NLP that serves as a cost and time effective approach for hospitality and tourism businesses to better understand their customers' needs and sentiments through extracting and analyzing opinions on online review platforms such as TripAdvisor (Geetha *et al.*, 2017).

Sentiment analysis (or opinion mining) can be described as the field of study that analyses people's opinions, sentiments, and emotions towards a product, service, company, or any other subject (Liu, 2012). Text analytics usually identifies sentiments as positive, negative, or neutral (Mostafa, 2013). In recent years, hospitality and tourism scholars have been paying increasing attention to the application of sentiment analysis in social media studies (Xiang *et al.*, 2017; Yu *et al.*, 2021). Nakayama and Wan (2019) applied text mining software to conduct a sentiment analysis of restaurant reviews on both Yelp.com (English version) and Yelp.co.jp (Japanese version) based on the four aspects of dining experience, namely food quality, service, ambience, and price fairness. Their study revealed that cultural differences exist in how Japanese and Western customers generate review content and their perception of what makes a quality review. Similarly, taking into account cultural differences, Sann and Lai (2020) used sentiment analysis to study the type of service failures that come across by Asian and Non-Asian guests. Through an analysis of 390,236 complaint terms extracted from TripAdvisor posts about 353 hotels in the UK by guests from 63 nations, the results indicated that both Asian and Non-Asian guests often encountered service failures during occupancy, while the former was found to complain about equipment-related failures, and the latter more about housekeeping-related issues. Analyzing data on user's restaurant reviews from online platforms can represent huge benefits to companies and can make them turn negative reviewers into brand advocates. For this reason, there are studies, like Nave *et al.* (2018), that propose a Decision Support System (DSS) to help managers develop insights and define strategies that are more in line with the customers' expectations.

Conceptualization and research hypotheses

In general, previous studies on online restaurant reviews primarily focused on four fundamental aspects of service quality in restaurant operations, namely food, service, ambience, and price, as they are considered important factors influencing customers' dining experience and customer satisfaction (Alamoudi and Alghamdi, 2021; Nakayama and Wan, 2019; Ramanathan *et al.*, 2016; Yan *et al.*, 2015; Zhu *et al.*, 2019). Also, Nakayama and Wan (2019) suggested that these four aspects are proven to be relatively stable in restaurant reviews over time. Therefore, the sentiment analysis of restaurant reviews conducted in the present study is based on these four key attributes. By analyzing the sentiment around these four dimensions, we aim to understand which factors affect the overall sentiment the most. As the analysis is intended to investigate how the overall sentiment of customers changes when a restaurant receives a Michelin Star, the award of a Michelin Star is an important variable. This enabled us to pinpoint the date of the award and understand how the sentiment was before and after this date. Another variable that adds value to the analysis is how many stars a restaurant has. For instance, the impact of receiving the first Michelin Star might be different from a restaurant achieving an additional star. The star rating and local language variables allow us to get a deeper understanding of how the language of the review and the given star rating are correlated to the overall sentiment. Finally, we have the overall sentiment, which is a variable that depends on the remaining ones.

According to Yoon *et al.* (2019), consumers are influenced by others' reviews, meaning that when consumers review a restaurant, they pay attention to the experiences and opinions of others. This suggests that there is a social influence in writing online reviews. Accordingly, we posit that the award of a Michelin Star will increase the overall sentiment towards the restaurant:

H1a. The award of Michelin Star increases consumers' overall sentiment towards a restaurant in terms of written reviews.

H1b. The award of Michelin Star increases consumers' overall sentiment towards a restaurant in terms of star rating.

According to Pacheco (2018), food and service are significant factors that affect customers' overall satisfaction in the segment of Michelin-starred restaurants. Moreover, consumers tend to hold higher expectations for this type of restaurants (Chiang and Guo, 2021). Therefore, we propose:

H2. Sentiment towards food is affected by the award of a Michelin Star.

H3. Sentiment towards service is affected by the award of a Michelin Star.

Although the mechanical aspect, such as ambience, may contribute to one's dining experience (Berry *et al.*, 2006), it does not always affect customer satisfaction in the context of fine-dining (Arora and Singer, 2006; Pacheco, 2018). Hence, we propose that:

H4. Sentiment towards ambience is not affected when a restaurant is awarded a Michelin Star

Based on Aron *et al.* (2013)'s self-expansion theory, Liu *et al.* (2022) found that consumers are willing to pay a higher price to dine at a Michelin-starred restaurant for the social, unique and luxurious values that this type of restaurant offers. Given consumers' willingness to pay more, we propose the following hypothesis:

H5. Sentiment towards price is not affected by the award of a Michelin Star.

Methodology

The dataset

The data analyzed in the current study were collected from TripAdvisor (www.tripadvisor.com), an online platform that allows users to review restaurants and other hospitality and tourism services. The list of Michelin-starred restaurants was obtained from www.viamichelin.com, which also includes information on the number of Michelin stars, type of cuisine, and location.

The criteria for restaurants to be included in the analysis are as follows: (1) Restaurants with a total of more than 20 reviews in the six months prior to and following the award of a Michelin Star; (2) The difference between the number of reviews before and after the award should be small, in which one period represented 70% or more of the total amount of reviews will be excluded.

For this analysis, a list of 35 restaurants awarded a star in the 2018 Michelin Guide was created. The restaurants included in the analysis are in Europe and have 1, 2, or 3 Michelin stars by the time of the release of the 2018 Michelin Guide (Table 1).

Moreover, a list of 2,316 reviews related to these restaurants was retrieved from TripAdvisor. In addition, a list of 52 restaurants that were not awarded a star but are similar in price, rating, location, and cuisine, was added to be used as a control group. Finally, 6,555 reviews about these restaurants were also retrieved (Table 2).

From the 35 Michelin restaurants, 2,316 English reviews were extracted from TripAdvisor. These reviews spanned a period of one year, where six months were prior to the restaurant obtaining the Michelin Star, and six months after that event. In doing so we attempted to control other factors that might explain variations in the sentiment other than obtaining the award. On the other hand, six months allowed us to have a considerable number of reviews. The awards were given on different dates depending on the country. Table 3 summarises the dates for each country.

Of the total number of reviews in the Michelin Group, 77.5% were given to restaurants that received their first star in 2018, 18.3% to restaurants that received their second star, and 4.2% to restaurants that received their third star, respectively as shown in Table 4.

Analytical tools and procedures

The collected raw data were filtered, transformed, mined, and finally, interpreted to be converted into information. Information from TripAdvisor was extracted using a web crawler developed by Beautiful Soup, a Python library for parsing HTML. For each restaurant, information extracted were restaurant name, price range, text review, star review, and date of the visit. Restaurant names and price ranges are provided by the restaurant representative (manager or owner), and can be used to categorize restaurants. Reviews are provided by users, and these are sets of unstructured data that need to be processed after crawling. Date of the visit is also provided by users and can be used to segment them. For this step, we used a python script that crawled TripAdvisor's website, getting the name of the restaurant, date of the visit, star review, and a written review. After getting the reviews, those were stored in CSV (comma-separated values) files and, later, uploaded to a sentiment analysis software.

Subsequently, data processing was performed using Semantria (e.g. Santos *et al.*, 2018). Semantria uses lexicon-based linguistic information and rules to detect sentiments in short

Table 1.
Number of restaurants in the sample

Group (87)	Number of stars	# Restaurants	% of group	% of total
Control group (52)	0	52	100%	59.8%
Michelin group (35)	1	26	74.3%	40.2%
	2	6	17.1%	
	3	3	8.6%	

Table 2.
Geographic distribution of the restaurants and reviews

	Michelin group		Control group	
Country	# Restaurants	# Reviews	# Restaurants	# Reviews
United Kingdom	8	943	12	2,627
Spain	6	334	8	486
Italy	6	231	7	597
Austria	4	179	8	533
Germany	3	196	4	337
France	2	63	4	642
Netherlands	2	133	2	293
Sweden	1	20	1	59
Denmark	1	22	2	119
Hungary	1	171	2	563
Finland	1	22	2	299
Total	35	2,316	52	6,555

Country	Date of award
United Kingdom	17 October, 2017
Spain	27 November, 2017
Italy	16 November, 2017
Austria	26 March, 2018
Germany	15 November, 2017
France	5 February, 2018
Netherlands	11 December, 2017
Sweden	19 February, 2018
Denmark	19 February, 2018
Hungary	26 March, 2018
Finland	19 February, 2018

Table 3. Date of Michelin Star award per country

	# of stars	Time of review	# Reviews	% of subtotal	Average sentiment	Standard deviation	% of group total
Control group	0	After award	3,083	47.0%	0.65	0.43	100%
		Before award	3,472	53.0%	0.66	0.42	
		Total	6,555	–	0.65	0.42	
Michelin group	1	After award	845	47.1%	0.51	0.33	77.5%
		Before award	950	52.9%	0.54	0.36	
		Total	1,795	–	0.52	0.34	
	2	After award	222	52.4%	0.53	0.31	18.3%
		Before award	202	47.6%	0.57	0.34	
		Total	424	–	0.55	0.32	
	3	After award	45	46.4%	0.42	0.34	4.2%
		Before award	52	53.6%	0.42	0.33	
		Total	97	–	0.42	0.34	
	Group total	After award	1,112	48.0%	0.51	0.32	100%
		Before award	1,204	52.0%	0.54	0.36	
		Total	2,316	–	0.52	0.34	
			8,871				

Table 4. Detailed review information per group before and after the award

sentences, and lexical chains to create topic-specific summaries in text. Semantria uses synonym expansion and other techniques to construct chains of topics in pieces of text (Lexalytics, n.d.-b). Semantria also analyses entire documents (reviews) and gives them a sentiment score from -3 to 3, and components (queries, entities, or topics) from -10 to 10, where the negative end represents an extremely negative sentiment and the positive end an extremely positive sentiment. This range varies depending on the configuration. These documents and components also receive a tag (negative, neutral, or positive) depending on the sentiment score. A document sentiment is considered negative when it is lower than -0.05 and positive when it is greater than 0.22 (the remaining are neutral). A component sentiment is negative when it is lower than -0.45 and positive when it is greater than 0.5. The software also uses modifiers that affect the sentiment, such as intensifiers (very, a lot, super, etc.) and negators (not, never, etc.). Moreover, Semantria has industry packs which contain queries, topics, and categories that are related to the restaurant industry. Some words might be seen as negative in a certain context, but they can also be positively perceived in the restaurant world. One example could be the word "explosion", which has a negative connotation in general; however, in the restaurant world, the phrase "explosion of flavors" is commonly used. For this reason, industry packs are essential for the analysis. Here we crossed both sources of data, organized and prepared the data to perform the sentiment analysis. The properties of our data set are described in Table 5.

To process the data, the reviews had to be uploaded into a tokenization algorithm, in which the reviews were broken into words, phrases, symbols and other elements which are called tokens. In this process, the words were normalized, all letters were turned into lower case and all symbols and numbers were removed. Also, words like "loved" and "loving" were turned into "love" (verb). Then each word was tagged with a type (noun, verb, or adjective) and categorized according to Lexalytics concept topics (Lexalytics, n.d.-a) and user-defined ones (see Figure 1). Subsequently, these words were matched with a large set of words, and sentiments were applied to those (positive, negative, or neutral) based on sentences inside a review.

After the pre-processing stage, data were analyzed. During this step, we not only analyzed the reviews in general but also took into consideration the most relevant dimensions: price, food quality, waiting time, waiters service, the physical environment and other dimensions that came up during the analysis. Afterward, we grouped them in the four dimensions that we identified earlier: price, food, service, and ambiance. These steps enabled us to understand the sentiment around the four main dimensions. To do so, we created a taxonomy in Semantria with the help of an industry pack that allowed us to group queries and dimensions in a hierarchical way as shown in Figure 1. This means that dimensions and queries were grouped under a parent dimension and the sentiment around them represented the sentiment around the main one, i.e. our four main dimensions.

Results

Overall sentiment in the form of written reviews

As shown in Figure 2, the overall sentiment towards restaurants in both the control group and the Michelin group exhibits a decrease from one period to another. In the control group, the decrease was 2.1%, and in the 1- and 2-star restaurants, the decrease was about 5%. In the 3-star restaurants, the decrease was less than 1%, but this category represents only 4.2% of the group's reviews. The average decrease in the Michelin Group was 4.8%.

Category	Property	Description
Restaurant	Restaurant name	The name of the restaurant
	Michelin stars	The number of Michelin stars the restaurants have at the date of this analysis, after the award
	Restaurant location	The location of the restaurant
	Price range	The restaurant price range extracted from the Michelin website
Review	Star rating	The quantitative part of the review–a rating that ranges between 1 and 5
	Written review	The qualitative part of the review–a type of unstructured data where we conducted a sentiment analysis. Here, we only considered reviews written in English
	Date of visit	The reviewer's visit date. We only considered reviews given 6 months before and after the award. This allowed us to narrow the time frame, eliminate other factors that could lead to eventual changes and increase the likelihood of the changes being a result of the award
	After award	This is a binary property to separate the reviews given before (0) and after the award (1)
	Local language	This is a binary property that separates reviews written in the local language of the country (1), i.e. English in the United Kingdom, from reviews written in English where it is not the local language (0)

Table 5.
Description of dataset properties

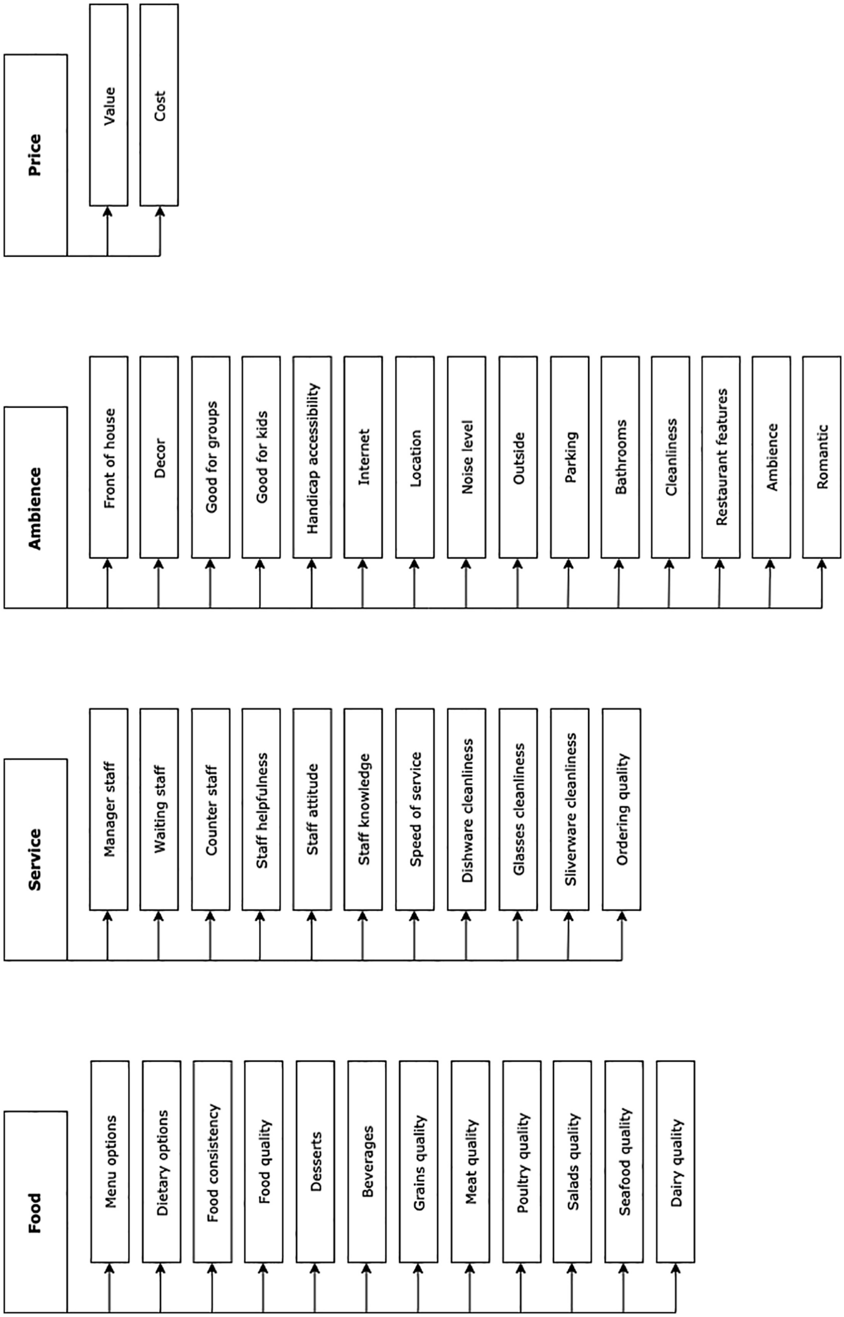


Figure 1.
Semantria taxonomy queries grouped into our four dimensions

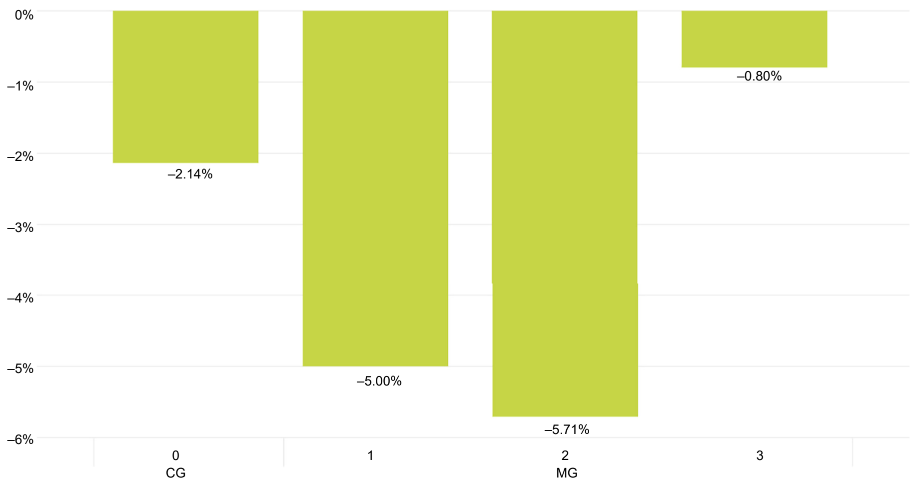


Figure 2.
Change in average sentiment from before to after the award in the control group (CG) and Michelin group (MG)

A sentiment tag (i.e. positive, negative, or neutral) was attributed to each review. Figure 3 shows that the percentage of positive reviews decreased after the date the Michelin Star was awarded, while the number of neutral and negative reviews increased, which is consistent with the pattern identified in Figure 2. An increase in the percentage of neutral and negative reviews and a decrease in percentage of positive reviews may explain a decrease in the overall sentiment after the award.

Although the overall sentiment in both groups decreased after the award of a Michelin Star, the decrease in the Michelin Group was 2.7% higher, doubling the decrease in the Control Group. Hence, H1a is rejected.

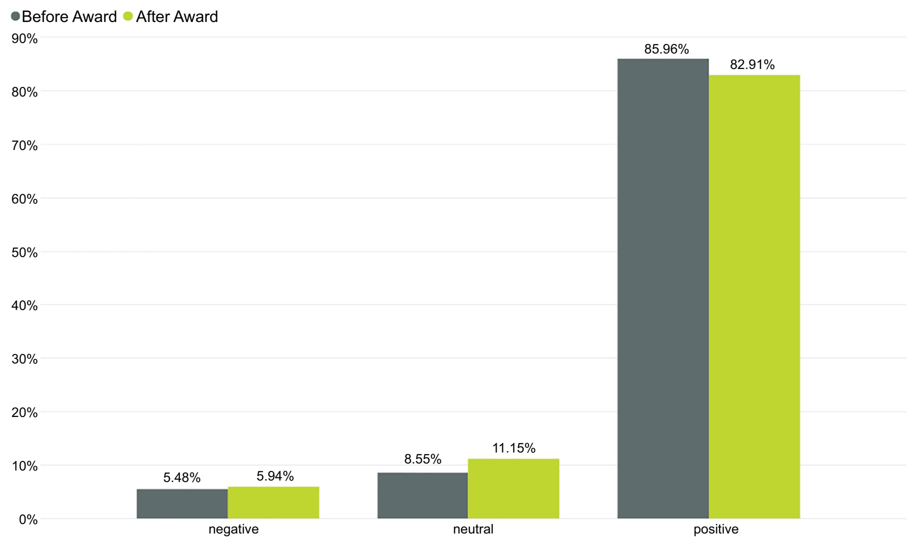


Figure 3.
Reviews per sentiment before and after the award (Michelin group)

Overall sentiment in the form of star rating

As previously mentioned, apart from written reviews, star rating of each review was also extracted from TripAdvisor. The average sentiment (indicated with a dot in Figure 4) increased as the star rating increased, except in 1- and 2-star ratings. It is shown that only the sentiment of those who gave 2 stars was negative. The sentiment of those who rated 1 star was neutral, but highly close to negative. The sentiment of those who rated 3 stars was neutral, and of those who rated 4 and 5 stars were positive. Therefore, average sentiment is nearly consistent with star rating.

Most of the reviews (87.9%) rated the restaurants with 4 or 5 stars (see Table 6), in which 71.6% rated the restaurants with 5 stars, resulting in an average of 4.5 out of 5. Moreover, when analysing the reviews before and after the award, the average rating was the same, i.e. 4.5, which did not show any changes in customers' sentiment when a restaurant was awarded a Michelin Star. Therefore, H1b is rejected.

Sentiment analysis towards the four key aspects: food, service, ambience, and price

From the 2,316 reviews of restaurants in the Michelin group, 13,618 sentiments about service, food, ambiance, and price were extracted. Of these sentiments, food and service were the most mentioned items, accounting for 41.4 and 40.5%, respectively, followed by ambience (11.4%), and price (6.8%). Also, sentiment analysis for each dimension before and after the award shows that the average sentiment decreased in each dimension except for price, where it increased from 0.18 to 0.30, falling within neutral values. However, price sentiment only consisted of a relatively small proportion (6.8%) of the total sentiments (see Table 7).

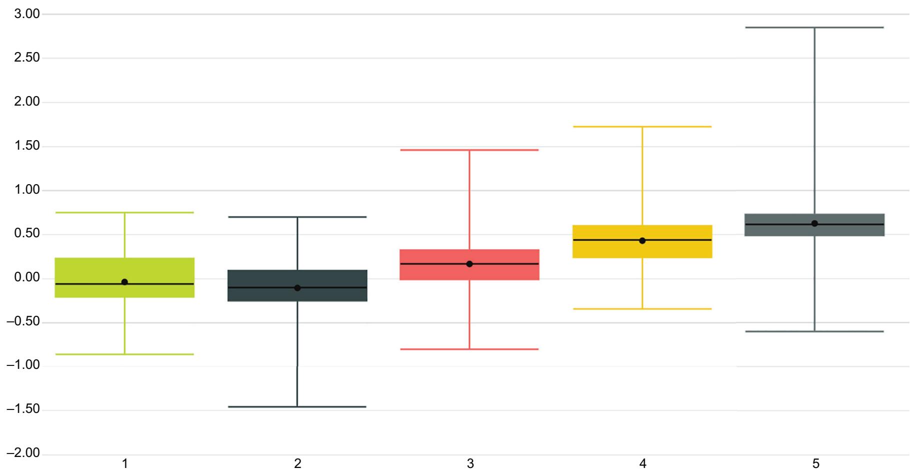


Figure 4. Review sentiments per star rating (from 1 to 5) with minimum and maximum value (whisker), average as dot, median as line and the interquartile range as interval

Table 6. Reviews' star rating

Star rating	# Reviews	% of total	Average sentiment	Standard deviation	Average rating
1	51	2.2%	–0.04	0.33	4.5
2	75	3.2%	–0.10	0.35	
3	156	6.7%	0.17	0.31	
4	377	16.3%	0.43	0.28	
5	1,657	71.6%	0.63	0.27	
Total	2,316	100.0%			

Table 7.
Detailed sentiment information per dimension (Michelin group)

Dimension	Time of review	# Sentiments	% of subtotal	Average sentiment	Standard deviation	% of total
Service	After award	2,647	48.0%	0.99	1.15	40.5%
	Before award	2,866	52.0%	1.14	1.22	
	Total	5,513	–	1.07	1.19	
Price	After award	420	45.6%	0.30	0.92	6.8%
	Before award	501	54.4%	0.18	1.09	
	Total	921	–	0.23	1.02	
Food	After award	2,798	49.7%	0.78	1.00	41.4%
	Before award	2,837	50.3%	0.86	1.01	
	Total	5,635	–	0.82	1.01	
Ambiance	After award	762	49.2%	0.57	0.86	11.4%
	Before award	787	50.8%	0.60	0.85	
	Total	1,549	–	0.59	0.86	
Total	After award	6,627	48.7%	0.81	1.06	100%
	Before award	6,991	51.3%	0.89	1.12	
	Total	13,618	–	0.85	0.86	

Figure 5 shows changes in the sentiment towards each dimension for control group and different categories under the Michelin group (i.e. 1-, 2-, and 3-starred Micheline restaurants), in which changes in the control group were slight, varying between −3.2% and −6.4%, while the changes in the Michelin group were rather pronounced. Particularly, the sentiments towards price increased by a relatively large amount for restaurants that won their first or third star (approximately 70%) and increased by about 29% for restaurants that won their second star. Interestingly, there was an evident decrease in the ambience sentiment in the 2-starred Micheline restaurants (−40.2%). In terms of food and service, sentiments exhibited a mild to moderate decrease, particularly in the 2- (food and service: approximately −21% respectively) and 3-starred Michelin restaurants (food: −23.6%; service: −15.4%).

In terms of overall changes, the patterns are consistent with those in Figure 5 (see Figure 6). Meanwhile, the increase in sentiment towards price was significantly higher in the Michelin group, and the decrease in sentiment towards other dimensions was also apparent in the Michelin group, except for the ambience sentiment which exhibited a mild decrease. In addition,

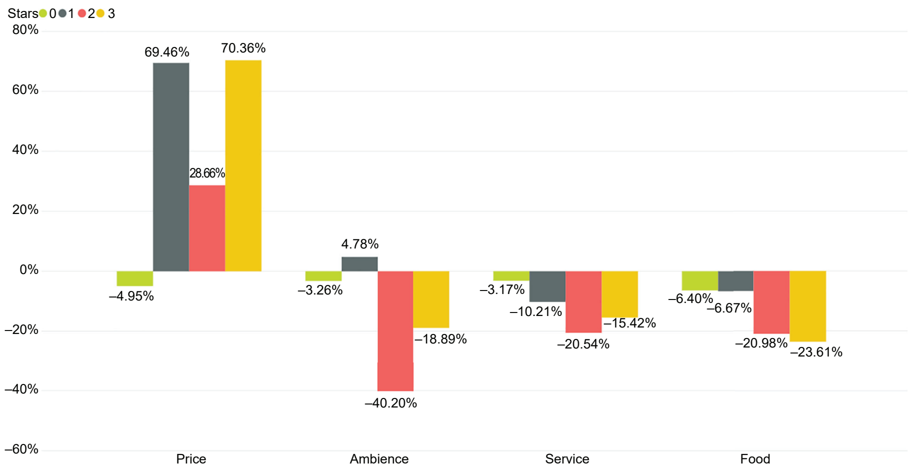
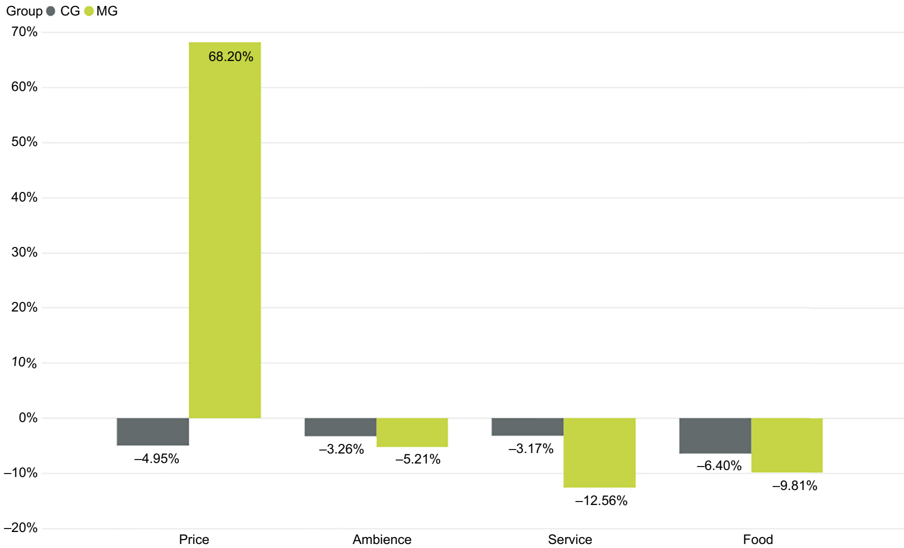


Figure 5.
Change in sentiments per dimension (price, ambience, service and food) and restaurant stars before and after the award of 1, 2 or 3 stars



Note(s): Control group in grey and Michelin Group in green

Figure 6. Change in sentiments per dimension (price, ambience, service and food) and restaurant group – control group in grey and Michelin group in green

it is worth pointing out that one-Michelin-starred restaurants experienced a mild increase (4.8%), yet two-Michelin-starred restaurants saw an evident decrease (−40.2%) in the ambience sentiments. Therefore, H2 and H3 are supported, while H4 and H5 are rejected.

Discussion

Nowadays, it has become a common practice that consumers take into consideration online reviews before purchasing a product or service, particularly the purchase of fine-dining services such as a meal at a Michelin-starred restaurant given its intangible nature and the risk associated with the purchase such as financial risk (Chiang and Guo, 2021). Moreover, Zhang *et al.* (2010) suggested that consumers tend to find consumer-generated reviews more reliable than editor reviews, asserting the importance of e-WOM. Therefore, it is of fundamental importance to understand what factors affect consumers' review sentiments on online review platforms. Specifically, this study investigated how online review sentiments changed after restaurants were awarded a Michelin Star in order to shed light on how the award of Michelin Star affects online reviews as well as what factors contribute to positive online restaurant reviews.

Changes in the online sentiment after the award of a Michelin Star

The award of a Michelin Star is usually considered beneficial for restaurants such as enhanced reputation and awareness (Chiang and Guo, 2021). Moreover, it may serve as a competitive advantage for attracting wider markets such as international tourists (Batat, 2021). Nevertheless, this may not be the case in the realm of online review platforms. Our findings revealed decrease in the average online sentiment after the award of a Michelin Star. Specifically, sentiment towards 2-star Michelin restaurants experienced the greatest decrease, closely followed by 1-star Michelin restaurants. Regarding sentiment orientation, there was also decrease in positive review sentiments, yet increase in both negative and neutral sentiments. This may be explained by the fact that consumers tend to develop higher expectations for Michelin-starred restaurants (Chiang and Guo, 2021), and accordingly, customer satisfaction will be negatively affected if one's expectation is not met (Arora and Singer, 2006).

In particular, consistent with Pacheco (2018)'s findings, food and service sentiments were both affected by the award of a Michelin Star, in which service sentiment was the most affected aspect, followed by food. Again, this may be attributed to the increased expectations of customers (Chiang and Guo, 2021) and their important role in customer satisfaction (Liu and Jang, 2009).

In contrast to our hypotheses, ambience sentiment was also slightly affected by the award of a Michelin Star. Although previous studies suggested that ambience is not a significant factor determining customer satisfaction (Arora and Singer, 2006), it contributes to one's dining experience (Berry *et al.*, 2006; Chua *et al.*, 2014). Also, customers tend to dine at a Michelin-starred restaurant for its unique and luxurious experience, which is created by not only food and service, but also ambience (Liu *et al.*, 2022). Specifically, sentiment towards the ambience aspect of two-Michelin-starred restaurants was highly negatively affected. One possible explanation for this result is that restaurants maintained the same ambience when obtaining an additional Michelin Star, yet customers expected to experience something different from this upgrade.

Interestingly, we found that price sentiment was positively affected by the award of a Michelin Star, with a prominent increase of 68.2%. This surprising result may be due to the luxurious values perceived by customers. As mentioned previously, customers who dine at a Michelin-starred restaurant are willing to pay a higher price because they perceive that such luxury consumption will bring them a sense of social status and unique experiences (Liu *et al.*, 2022). Moreover, Kiatkawsin and Han (2019) suggested that luxury restaurants, Michelin-starred restaurants in particular, often have the edge in premium pricing over non-luxury restaurants; meanwhile, competitive pricing may backfire because prestige, exclusive and unique experiences are what luxury dining patrons value.

Conclusion

Theoretical implications

Our work made three main theoretical contributions. First, this study extends extant literature by investigating changes in customer sentiments towards four fundamental aspects (i.e. food, service, ambience, and price) before and after a restaurant has received a Michelin Star. Second, it adopted a novel approach by using data extracted from TripAdvisor to conduct a sentiment analysis of online reviews for Michelin-starred restaurants, which contributes to identifying aspects that are most or least affected by the award of a Michelin Star. Third, this study contributes to the literature on customer satisfaction of Michelin-starred restaurants in the online review context by also highlighting the role of ambience; albeit a small role, it should not be overlooked by researchers in the field.

Managerial implications

With the growth of online social media, writing online reviews to share user experience and relying on others' reviews to inform purchase decision-making are common practices for consumers. This sentiment analysis provides valuable insights into key aspects that Michelin-starred restaurant operators and owners need to pay attention in order to create a unique and compelling gastronomic experience that will surprise their customers, leave a lasting impression, and trigger positive online restaurant reviews. The results of our study argue that consumers tend to hold higher expectations for this type of upscale restaurants given its recognition and quality assurance, so they are more likely to have negative feelings when their expectations are disconfirmed. Therefore, restaurants should continuously improve their food, and service while paying attention to small details such as ambience, through creativity and innovation. For example, in addition to food quality and outstanding service that are the basics of any Michelin-starred restaurant, culinary creativity should be emphasized, such as the artistic presentation of dishes, the use of new culinary techniques and unique ingredients. As suggested by Jeong and Jang (2011), dish presentation, employee appearance, décor and ambience that are visually appealing may influence customers' post-dining behavior, such as writing positive online reviews. In terms of pricing, high-end restaurants, especially Michelin-starred restaurants, have the edge in premium pricing, yet competitive pricing may backfire considering the luxurious values perceived by their patrons. In addition, people are more motivated to write online reviews of luxury dining consumption to conspicuously affiliate themselves with high-status restaurant (Kovács and Horwitz, 2018).

Limitations and future research

This study demonstrated that the overall sentiments decreased after restaurants were awarded a Michelin Star, in which service sentiment was the most affected aspect, followed by food and ambience. Yet, price sentiment showed a prominent increase. These findings could be explained by customers' increased expectations and perceived luxurious values that lead to the willingness to pay more.

The present work is not without limitations. First, this study was based on a sample of reviews on European restaurants, but the important role of cultural differences in shaping customer reviews could not be ignored (Nakayama and Wan, 2019). Therefore, future work may investigate how the Michelin award affects sentiments toward the four key dimensions in different geographical areas, such as Japan, the United States and China, as these are some of the countries with the highest number of Michelin-starred restaurants (Chefs 'Pencil, 2021). Second, the inclusion of factors such as age, gender, fine-dining occasion and income could further improve the value of a future study. Third, the reasons attributed to the change in customers' sentiment may require further empirical testing to better understand customers' post-dining behavior.

References

Alamoudi, E.S. and Alghamdi, N.S. (2021), "Sentiment classification and aspect-based sentiment analysis on yelp reviews using deep learning and word embeddings", *Journal of Decision Systems*, Vol. 30 Nos 2-3, pp. 259-281.

Alcoba, J., Mostajo, S., Paras, R., Ebron, R.A. and Balderas-Cejudo, A. (2020), "On finding the voice of the customer in the digital traces of the Michelin-star gastronomy experience: unveiling insights for service design", *International Conference on Exploring Services Science*, pp. 21-34.

Amelia, M. and Garg, A. (2016), "The first impression in a fine-dining restaurant. A study of C restaurant in Tampere, Finland", *European Journal of Tourism, Hospitality, and Recreation*, Vol. 7 No. 2, pp. 100-111.

Aron, A., Lewandowski, G.W. Jr, Mashek, D. and Aron, E.N. (2013), "The self-expansion model of motivation and cognition in close relationships", in Simpson, J.A. and Campbell, L. (Eds), *The Oxford Handbook of Close Relationships*, Oxford University Press, pp. 90-115.

Arora, R. and Singer, J. (2006), "Customer satisfaction and value as drivers of business success for fine dining restaurants", *Services Marketing Quarterly*, Vol. 28 No. 1, pp. 89-102.

Banerjee, S., Bhattacharyya, S. and Bose, I. (2017), "Whose online reviews to trust? Understanding reviewer trustworthiness and its impact on business", *Decision Support Systems*, Vol. 96, pp. 17-26, doi: 10.1016/J.DSS.2017.01.006.

Batat, W. (2021), "The role of luxury gastronomy in culinary tourism: an ethnographic study of Michelin-Starred restaurants in France", *International Journal of Tourism Research*, Vol. 23 No. 2, pp. 150-163.

Berry, L.L., Wall, E.A. and Carbone, L.P. (2006), "Service clues and customer assessment of the service experience: lessons from marketing", *Academy of Management Perspectives*, Vol. 20 No. 2, pp. 43-57.

Bilgihan, A., Seo, S. and Choi, J. (2018), "Identifying restaurant satisfiers and dissatisfiers: suggestions from online reviews", *Journal of Hospitality Marketing and Management*, Vol. 27 No. 5, pp. 601-625.

Chef's Pencil (2021), "Countries with the highest density of michelin-starred restaurants - Chef's Pencil", available at: https://www.chefspencil.com/density-of-michelin-starred-restaurants/.

Chen, A. and Peng, N. (2018), "Examining consumers' intentions to dine at luxury restaurants while traveling", *International Journal of Hospitality Management*, Vol. 71, pp. 59-67, doi: 10.1016/J.IJHM.2017.11.009.

Chiang, C.F. and Guo, H.W. (2021), "Consumer perceptions of the Michelin guide and attitudes toward Michelin-starred restaurants", *International Journal of Hospitality Management*, Vol. 93, p. 102793, doi: 10.1016/J.IJHM.2020.102793.

Chua, B.-L., Jin, N., Lee, S. and Goh, B. (2014), "Influence of mechanic, functional, and humanic clues on customers' experiential values and behavioral intentions in full-service restaurants", *Journal of Foodservice Business Research*, Vol. 17 No. 2, pp. 67-84.

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.

Garg, A. and Amelia, M. (2016), "Service clues' influence on customers' dining experience in fine dining restaurants", *Asia-Pacific Journal of Innovation in Hospitality and Tourism*, Vol. 5 No. 1, pp. 91-109.

Geetha, M., Singha, P. and Sinha, S. (2017), "Relationship between customer sentiment and online customer ratings for hotels - an empirical analysis", *Tourism Management*, Vol. 61, pp. 43-54, doi: 10.1016/J.TOURMAN.2016.12.022.

Gretzel, U. and Yoo, K.H. (2008), "Use and impact of online travel reviews", *Information and Communication Technologies in Tourism 2008*, pp. 35-46.

Guerreiro, J. and Rita, P. (2020), "How to predict explicit recommendations in online reviews using text mining and sentiment analysis", *Journal of Hospitality and Tourism Management*, Vol. 43, pp. 269-272, doi: 10.1016/J.JHTM.2019.07.001.

Harrington, R.J., Fauser, S.G., Ottenbacher, M.C. and Kruse, A. (2013), "Key information sources impacting Michelin restaurant choice", *Journal of Foodservice Business Research*, Vol. 16 No. 3, pp. 219-234.

Hennig-Thurau, T., Malthouse, E.C., Friege, C., Gensler, S., Lobschat, L., Rangaswamy, A. and Skiera, B. (2010), "The impact of new media on customer relationships", *Journal of Service Research*, Vol. 13 No. 3, pp. 311-330.

Hu, X. and Yang, Y. (2021), "What makes online reviews helpful in tourism and hospitality? A bare-bones meta-analysis", *Journal of Hospitality Marketing and Management*, Vol. 30 No. 2, pp. 139-158.

Hwang, J. and Ok, C. (2013), "The antecedents and consequence of consumer attitudes toward restaurant brands: a comparative study between casual and fine dining restaurants", *International Journal of Hospitality Management*, Vol. 32 No. 1, pp. 121-131, doi: 10.1016/J.IJHM.2012.05.002.

Jeong, E.H. and Jang, S.C.S. (2011), "Restaurant experiences triggering positive electronic word-of-mouth (eWOM) motivations", *International Journal of Hospitality Management*, Vol. 30 No. 2, pp. 356-366, doi: 10.1016/J.IJHM.2010.08.005.

Kiatkawsin, K. and Han, H. (2019), "What drives customers' willingness to pay price premiums for luxury gastronomic experiences at Michelin-starred restaurants?", *International Journal of Hospitality Management*, Vol. 82, pp. 209-219, doi: 10.1016/J.IJHM.2019.04.024.

Kiatkawsin, K. and Sutherland, I. (2020), "Examining luxury restaurant dining experience towards sustainable reputation of the Michelin restaurant guide", *Sustainability*, Vol. 12 No. 5, p. 2134, doi: 10.3390/SU12052134.

Kovács, B. and Horwitz, S. (2018), "Conspicuous reviewing: affiliation with high-status organizations as a motivation for writing online reviews", *Socius*, Vol. 4, p. 2378023118776848.

Lee, J.H. and Hwang, J. (2011), "Luxury marketing: the influences of psychological and demographic characteristics on attitudes toward luxury restaurants", *International Journal of Hospitality Management*, Vol. 30 No. 3, pp. 658-669, doi: 10.1016/J.IJHM.2010.12.001.

Lee, J. and Kim, Y.K. (2020), "Online reviews of restaurants: expectation-confirmation theory", *Journal of Quality Assurance*, Vol. 21 No. 5, pp. 582-599.

Lexalytics (n.d.-a), "Categorization | Lexalytics", available at: https://www.lexalytics.com/technology/categorization (accessed 15 March 2022).

Lexalytics (n.d.-b), "Data analytics with NLP and text analytics | Lexalytics", available at: https://www.lexalytics.com/ (accessed 15 March 2022).

Libai, B., Bolton, R., Bügel, M.S., De Ruyter, K., Götz, O., Risselada, H. and Stephen, A.T. (2010), "Customer-to-customer interactions: broadening the scope of word of mouth research", *Journal of Service Research*, Vol. 13 No. 3, pp. 267-282.

Litvin, S.W., Goldsmith, R.E. and Pan, B. (2008), "Electronic word-of-mouth in hospitality and tourism management", *Tourism Management*, Vol. 29 No. 3, pp. 458-468.

Liu, Y. and Jang, S.C (2009), "Perceptions of Chinese restaurants in the U.S.: what affects customer satisfaction and behavioral intentions?", *International Journal of Hospitality Management*, Vol. 28 No. 3, pp. 338-348, doi: 10.1016/J.IJHM.2008.10.008.

Liu, C.R., Kuo, T.M., Wang, Y.C., Shen, Y.J., Chen, S.P. and Hong, J.W. (2022), "Perceived luxurious values and pay a price premium for Michelin-starred restaurants: a sequential mediation model with self-expansion and customer gratitude", *International Journal of Hospitality Management*, Vol. 103, p. 103185, doi: 10.1016/J.IJHM.2022.103185.

Liu, B. (2012), "Sentiment analysis and opinion mining", *Synthesis Lectures on Human Language Technologies*, Vol. 5 No. 1, pp. 1-167, 9781608458844.

Madeira, A., Palrão, T., Mendes, A.S. and Ottenbacher, M.C. (2022), "The culinary creative process of Michelin Star chefs", *Tourism Recreation Research*, Vol. 47 No. 3, pp. 258-276.

Meek, S., Wilk, V. and Lambert, C. (2021), "A big data exploration of the informational and normative influences on the helpfulness of online restaurant reviews", *Journal of Business Research*, Vol. 125, pp. 354-367.

Michelin Guide (n.d.a), "About us. Michelin guide", available at: https://guide.michelin.com/en/about-us (accessed 28 February 2022).

Michelin Guide (n.d.b), "What the Michelin guide's symbols mean", available at: https://guide.michelin.com/th/en/to-the-stars-and-beyond-th (accessed 7 March 2022).

Mostafa, M.M. (2013), "More than words: social networks' text mining for consumer brand sentiments", *Expert Systems With Applications*, Vol. 40 No. 10, pp. 4241-4251.

Mudambi, S.M. and Schuff, D. (2010), "Research note: what makes a helpful online review? A study of customer reviews on Amazon. com", *MIS Quarterly*, Vol. 34 No. 1, pp. 185-200.

Nakayama, M. and Wan, Y. (2019), "The cultural impact on social commerce: a sentiment analysis on Yelp ethnic restaurant reviews", *Information and Management*, Vol. 56 No. 2, pp. 271-279, doi: 10.1016/J.IM.2018.09.004.

Nave, M., Rita, P. and Guerreiro, J. (2018), "A decision support system framework to track consumer sentiments in social media", *Journal of Hospitality Marketing and Management*, Vol. 27 No. 6, pp. 693-710.

Pacheco, L.M. (2018), *An Analysis of Online Reviews of Upscale Iberian Restaurants*, Universidade Portucalense, Porto.

Patel, R. and Patel, S. (2021), "Deep learning for natural language processing", *Information and Communication Technology for Competitive Strategies (ICTCS 2020)*, Springer, pp. 523-533.

Ramanathan, R., Di, Y. and Ramanathan, U. (2016), "Moderating roles of customer characteristics on the link between service factors and satisfaction in a buffet restaurant", *Benchmarking: An International Journal*, Vol. 23 No. 2, pp. 469-486.

Rouliez, P., Tojib, D. and Tsarenko, Y. (2019), "The influence of online review exposure on reviewers' intensity level of negative word of mouth", *Journal of Hospitality and Tourism Research*, Vol. 43 No. 5, pp. 712-733.

Sann, R. and Lai, P.C. (2020), "Understanding homophily of service failure within the hotel guest cycle: applying NLP-aspect-based sentiment analysis to the hospitality industry", *International Journal of Hospitality Management*, Vol. 91, p. 102678, doi: 10.1016/J.IJHM.2020.102678.

Santos, C.L., Rita, P. and Guerreiro, J. (2018), "Improving international attractiveness of higher education institutions based on text mining and sentiment analysis", *International Journal of Educational Management*, Vol. 32 No. 3, pp. 431-447.

Svejenova, S., Mazza, C. and Planellas, M. (2007), "Cooking up change in haute cuisine: ferran Adrià as an institutional entrepreneur", *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior*, Vol. 28 No. 5, pp. 539-561.

Tsao, W.-C. and Hsieh, M.-T. (2015), "eWOM persuasiveness: do eWOM platforms and product type matter?", *Electronic Commerce Research*, Vol. 15 No. 4, pp. 509-541.

Van Doorn, J., Lemon, K.N., Mittal, V., Nass, S., Pick, D., Pirner, P. and Verhoef, P.C. (2010), "Customer engagement behavior: theoretical foundations and research directions", *Journal of Service Research*, Vol. 13 No. 3, pp. 253-266.

Vargas-Calderón, V., Moros Ochoa, A., Castro Nieto, G.Y. and Camargo, J.E. (2021), "Machine learning for assessing quality of service in the hospitality sector based on customer reviews", *Information Technology and Tourism*, Vol. 23 No. 3, pp. 351-379.

Vargas-Sanchez, A. and López-Guzmán, T. (2022), "Creative process and culinary experiences in Michelin-starred restaurants", *Journal of Culinary Science and Technology*, Vol. 20 No. 2, pp. 97-116.

Voss, K.E., Spangenberg, E.R. and Grohmann, B. (2003), "Measuring the hedonic and utilitarian dimensions of consumer attitude", *Journal of Marketing Research*, Vol. 40 No. 3, pp. 310-320.

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.

Westbrook, R.A. (1987), "Product/consumption-based affective responses and postpurchase processes", *Journal of Marketing Research*, Vol. 24 No. 3, pp. 258-270.

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, doi: 10.1016/J.TOURMAN.2016.10.001.

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.

Yang, W. and Mattila, A.S. (2016), "Why do we buy luxury experiences? Measuring value perceptions of luxury hospitality services", *International Journal of Contemporary Hospitality Management*, Vol. 28 No. 9, pp. 1848-1867.

Yoon, Y., Kim, A.J., Kim, J. and Choi, J. (2019), "The effects of eWOM characteristics on consumer ratings: evidence from TripAdvisor. com", *International Journal of Advertising*, Vol. 38 No. 5, pp. 684-703.

Yu, T., Rita, P., Moro, S. and Oliveira, C. (2021), "Insights from sentiment analysis to leverage local tourism business in restaurants", *International Journal of Culture, Tourism and Hospitality Research*, Vol. 16 No. 1, pp. 321-336.

Zhang, Z., Ye, Q., Law, R. and Li, Y. (2010), "The impact of e-word-of-mouth on the online popularity of restaurants: a comparison of consumer reviews and editor reviews", *International Journal of Hospitality Management*, Vol. 29 No. 4, pp. 694-700, doi: 10.1016/J.IJHM.2010.02.002.

Zhu, F. and Zhang, X. (2010), "Impact of online consumer reviews on sales: the moderating role of product and consumer characteristics", *Journal of Marketing*, Vol. 74 No. 2, pp. 133-148.

Zhu, P., Chen, Z., Zheng, H. and Qian, T. (2019), "Aspect aware learning for aspect category sentiment analysis", *ACM Transactions on Knowledge Discovery from Data (TKDD)*, Vol. 13 No. 6, pp. 1-21.

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