Identifying the attributes of consumer experience in Michelin-starred restaurants: a text-mining analysis of online customer reviews

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Abstract

Purpose – The main goal of this paper is to identify the attributes of consumer experience in Michelin-starred restaurants and to estimate their effects on restaurant ratings.
Design/methodology/approach – A sample of 70,233 online reviews of 224 Spanish Michelin-starred restaurants were analysed with the latent Dirichlet allocation algorithm. A sentiment analysis and a logistic regression analysis were also employed to estimate the effect of attributes on restaurant ratings.
Findings – Customer attention, food quality, decor and ambience and value for money are frequently used to define restaurant experience. However, it is shown in this study that the experience in a Michelin-starred restaurant goes beyond the evaluation of those four attributes. Furthermore, the effect of the factors that were identified on customer satisfaction differed depending on the restaurant ratings.
Research limitations/implications – The findings are linked to the context of Spanish Michelin-starred restaurants. It is also assumed in this study that online reviews are based on truthful opinions.
Practical implications – Restaurant managers should primarily focus on customer attention and food quality to achieve customer satisfaction. In addition, those restaurants with an error-free service and a highly appreciated wine list among diners are more likely to achieve the culinary excellence that deserves a 5-star rating on TripAdvisor.
Originality/value – The attributes of the restaurant experience are frequently identified in literature reviews. Research based on text-mining analyses of customer reviews to discover *a posteriori* the factors that define a restaurant experience is scarce, and particularly difficult to find in the context of Michelin-starred restaurants.

Keywords Michelin-starred restaurants, Online reviews, Restaurant experience, Text-mining, Latent Dirichlet allocation, Sentiment analysis
Paper type Research paper

1. Introduction

Customer experience has its origin in the experience economy paradigm of Pine and Gilmore (1998), according to which, consumers seek to achieve a unique and memorable experience when they buy a product or service. According to these authors, the creation of positive, unique and memorable experiences leads to competitive advantages for a company that can differentiate its offer from the offers of other competitors. This paradigm has special relevance in the services sector and particularly in the hospitality and restaurant industry. Conceptually, customer experience is similar to the concept that Parasuraman *et al.* (1988)

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proposed of perceived service quality. Consumers make subjective evaluations of their current experience compared to the expected experience (Jeong and Jang, 2011). As a consequence, an emotional response is evoked in the consumer: either positive, neutral, or negative (Björk and Kauppinen-Räisänen, 2016).

Experiences are subjective and lived out with different intensities, in so far as they are based on the personal perceptions of each individual (Björk and Kauppinen-Räisänen, 2016). Therefore, the individual also assumes an active role in creating the experience (Gan *et al.*, 2017). Experiences are also linked to individual memories, which are more likely to be remembered when they are shared with other people or occur at a place or time of certain relevance, which is particularly true for gastronomic experiences (Björk and Kauppinen-Räisänen, 2016). For example, we tend to remember a birthday celebration, the first romantic dinner with our partner, a Christmas celebration with family, or a dinner at a fancy restaurant.

Researchers have highlighted the multidimensional nature of experiences (Björk and Kauppinen-Räisänen, 2014; Yrjölä *et al.*, 2019). The restaurant experience of the customer is particularly related to knowledge, observation and perceptions of restaurant attributes during their dining experience (Jeong and Jang, 2011; Mathayomchan and Taecharungroj, 2020). Therefore, one of the priority research objectives has been to determine the factors that comprise the restaurant experience. For the restaurant industry, knowing the attributes evaluated by consumers is important, in order to offer a positive gastronomic experience that achieves customer satisfaction, positive word of mouth and loyalty (Mathayomchan and Taecharungroj, 2020). At the same time, satisfaction with gastronomic experiences influences traveller satisfaction with the tourist destination (Jiménez-Beltrán *et al.*, 2016). Gastronomy that attracts the attention of tourists becomes an important reason for visiting a tourist destination (Castillo-Manzano *et al.*, 2021; Björk and Kauppinen-Räisänen, 2016) and making a significant contribution to its economic development (Pezenka and Weismayer, 2020). In particular, the gastronomic experience in a Michelin-starred restaurant may be the main reason for visiting a destination (Björk and Kauppinen-Räisänen, 2014).

The study of dining and restaurant experiences is well documented in the literature. Although there is no strict consensus, four main attributes are identified: food quality, customer service, decor and ambience and value for money (e.g. Jeong and Jang, 2011; Gan *et al.*, 2017; Liu and Tse, 2018; Yrjölä *et al.*, 2019; Mathayomchan and Taecharungroj, 2020; Aktas-Polat and Polat, 2021; Luo and Xu, 2021; Kim and Hwang, 2022, etc.). These attributes are also present in luxury-restaurant experiences, although consumers tend to have higher expectations with regard to performance at a luxury restaurant (Rita *et al.*, 2023). Thus, it has been suggested in previous studies that the characteristics of a luxury-restaurant experience are excellent food with distinctive presentations, high levels of service quality, a sophisticated and exclusive ambiance and high prices (Lee and Hwang, 2011; Chen and Peng, 2015; Yang and Mattila, 2016).

The conventional methodological approach used by researchers to analyse restaurant experiences has been the design of questionnaires based on the previous literature and administered to samples of restaurant consumers (e.g. Lee and Hwang, 2011; Jeong and Jang, 2011; Chen and Peng, 2015; Yrjölä *et al.*, 2019). However, the use of questionnaires and surveys has some notable drawbacks: higher costs and time for data collection, reduced number of responses and failure to reflect the restaurant experience in full (Vu *et al.*, 2019). In addition, according to Gan *et al.* (2017), the main drawback of this methodology is that the respondents are unlikely to describe their experiences as freely as they might in online restaurant reviews. Instead, their experience is conditioned by the questions and items that might appear in the questionnaire, and significantly biased results can be expected. Another methodological approach is based on the use of samples of customer-rated attributes evaluated on review websites (e.g. Zhang *et al.*, 2010; Yan *et al.*, 2015; Kim *et al.*, 2016).

However, the main limitation of these studies is that there may be other attributes of the restaurant experience, beyond those that appear on the website used for data collection.

More recently, some studies have analysed restaurant experience with text-mining techniques applied to massive volumes of online customer reviews. The main advantage of that approach is the identification of attributes, unlike those that are traditionally used to reflect the restaurant experience. However, some authors have previously identified the attributes from the existing literature using those qualitative analyses, with no reference to customer opinions (e.g. Gan *et al.*, 2017; Mathayomchan and Taecharungroj, 2020). In line with that approach, Rita *et al.* (2023) conducted a sentiment analysis of online reviews from restaurants with Michelin stars, but the attributes proposed were based on the theoretical findings of previous research.

Studies that have sought to determine the attributes of the restaurant experience *a posteriori*, analysing customer reviews with appropriate qualitative techniques are scarce (e.g. Pantelidis, 2010; Vu *et al.*, 2019; Pezenka and Weismayer, 2020; Luo and Xu, 2021; Nilashi *et al.*, 2021; Aktas-Polat and Polat, 2021), and more difficult to find, particularly in the context of Michelin-starred restaurants. To address that research gap, the main objective of this paper is to identify the principal attributes of customer experience in Michelin-starred restaurants. To that end, a sample of 70,233 online reviews of 224 Spanish restaurants in TripAdvisor was analysed with the latent Dirichlet allocation (LDA) algorithm. A lexicon-based sentiment analysis was then performed to estimate the customer evaluation of restaurant topics. Finally, the effects of the attributes on restaurant ratings were calculated using a logistic regression analysis. To the best knowledge of the author, this empirical study is the first to address customer experience at Michelin-starred Spanish restaurants with such a large sample of online reviews.

The structure of the paper is as follows. The literature will be reviewed in Section 2. The methodology and empirical work will be described in Section 3 and the results will then be presented in Section 4. Finally, the conclusions of the study and their implications will be discussed in Section 5.

2. Literature review

2.1 Consumer experience in Michelin-starred restaurants

The Michelin Guide is highly regarded as the most important gastronomic reference for critics, the general public and for restaurants themselves (Chiang and Guo, 2021). The first edition was published in France in 1900 by the brothers André and Edouard Michelin, founders of the Michelin tire company, and contained information to make travel easier for motorists: maps, instructions for changing a wheel, where to refuel and overnight accommodation offering meals. Interest in knowing the recommended restaurants grew over time, until the Michelin Guide had become a global reference in the field of gastronomy. Currently, over 30,000 establishments are rated in the Michelin Guide in over 30 countries across three continents. The countries with the highest number of restaurants awarded Michelin stars are the following: France (627), Japan (432), Italy (378), Germany (326), Spain (228) and the United States (206) (Michelin Guide, 2022).

The restaurants are awarded one, two and three stars following their evaluation in accordance with five universal criteria: "the quality of the ingredients, the harmony of flavours, the mastery of techniques, the personality of the chef as expressed through their cuisine and [. . .], consistency both across the entire menu and over time" (Michelin Guide, 2022). This evaluation is carried out by anonymous, independent and professional inspectors of different nationalities, who visit restaurants around the world without ever revealing their identity. One Michelin star denotes good food that is worth stopping for, two stars signify excellent food that is worth making an extra effort to find, and three stars indicate exceptional

food that is well worth the trip (Henderson, 2017). Restaurants awarded Michelin stars gain fame, recognition and prestige, significantly increasing the number of visitors who want to taste and to relish their cuisine (Chiang and Guo, 2021).

Michelin-starred restaurants have attracted the attention of researchers. Among the issues investigated, the following can be highlighted: the creative process in *haute-cuisine* restaurants (Vargas-Sanchez and López-Guzmán, 2022), the relationship between gastronomy tourism and Michelin-starred restaurants (Castillo-Manzano *et al.*, 2021; Batat, 2021; Madeira *et al.*, 2022), the restaurant websites (Daries *et al.*, 2018; Montargot *et al.*, 2022), brand communications on social media (Fissi *et al.*, 2022), the dimensions of sustainable food experiences offered in the luxury gastronomic industry (Batat, 2020), the effect of service excellence and guest delight on guest affective commitment (Panchapakesan *et al.*, 2022), and why consumers are willing to pay a price premium for a luxury gastronomic experience (Kiatkawsin and Han, 2019). Studies that have been directly focused on the factors evaluated during the dining experience in a Michelin-starred restaurant are scare. One exception is the research conducted by Rita *et al.* (2023). These authors considered that the four classic attributes of the restaurant experience identified in the literature review (food, service, ambience and price) were also suitable for measuring consumer experiences at Michelin-starred restaurants.

2.2 Online restaurant reviews

Electronic word-of-mouth or eWOM refers to informal communications between consumers on products, services and the companies that sell them through the Internet (Litvin *et al.*, 2008). Among the most important types of eWOM are the customer opinions posted on online review sites (Hennig-Thurau *et al.*, 2004). Positive online reviews and high ratings are associated with satisfied consumer experiences, increasing the likelihood of a purchase, whereas negative online reviews and low ratings are considered a type of customer complaint, which have the opposite effect (Vermeulen and Seegers, 2009). The influence of online reviews on firm performance has also been widely demonstrated. Customer ratings, for example, have a statistically positive relationship with sales of beers (Clemons *et al.*, 2006), books (Chevalier and Mayzlin, 2006) and hotel bookings (Ye *et al.*, 2009), etc.

Online reviews are especially important extra sources of information in the hospitality and restaurant industry, as the quality of each tourism product or service, due to its intangible nature, is difficult to assess before purchase and consumption (Litvin *et al.*, 2008). The ratings and comments that are posted on websites such as TripAdvisor.com, Yelp.com and Booking.com are consulted by travellers to reduce uncertainty and perceived purchase-related risks (Anderson, 2012). Those online reviews are also an excellent instrument for studying customer satisfaction with any one particular hotel or restaurant service (Kim *et al.*, 2015), because they are seen as more objective and wide-ranging information sources that are free of sample bias, as opposed to conventional questionnaires (Schuckert *et al.*, 2015).

In particular, online restaurant reviews usually have three components: (1) an overall customer rating; (2) customer ratings of different attributes including food quality, customer service, decor and value for money; and (3) positive and negative comments expressing customer opinions toward restaurant experiences. Researchers have usually collected these online reviews using web-scraping techniques. Although the purposes are diverse, two different research methodologies can be differentiated, depending on the nature of the data analysed. Quantitative methodologies are used in empirical studies based on samples of customer ratings, whose main objective is to analyse the effect of different attributes of the restaurant experience on various outcomes, such as restaurant popularity, revisit intention, restaurant performance, *etc.* On the other hand, qualitative methodologies are used in research studies based on the collection of customers' opinions. For example, topic modelling

has been used to identify the attributes that form the restaurant experience, while sentiment analysis is useful to quantify the customer satisfaction with these attributes. Topic modelling and sentiment analysis are complementary and frequently used with traditional quantitative methodologies (e.g. linear regression analysis, analysis of variance, logistic regression, etc.). Table 1 shows a review of empirical studies related to online restaurant reviews, detailing purposes, datasets, methodologies and major findings.

3. Research methodology

3.1 Data collection

The restaurant data collected were as follows: restaurant name, number of Michelin stars, restaurant rating and online reviews written in Spanish. That language was chosen to guarantee proper text-mining analysis without mixing opinions from different languages and, at the same time, to achieve a high number of online reviews. The web-scraping process was applied to TripAdvisor.com in October 2022. The result was a sample of 70,233 online reviews on 224 restaurants (Table 2), representing 98.24% of all Spanish restaurants mentioned in the Michelin Guide (2022).

3.2 Pre-processing of online reviews

Online review pre-processing took place in two phases. First, the online reviews were divided into sentences following the recommendations of previous studies (e.g. Gan *et al.*, 2017; Mathayomchan and Taecharungroj, 2020). The identification of topics with the LDA algorithm from online reviews can be problematic, as different attributes of the restaurant experience can be evaluated in the same review. Hence, it was assumed that sentences had a closer relation to a specific topic than a complete comment. Secondly, the sentence cleaning process was carried out, which generally implies the conversion of all words to lower case, the elimination of numeric characters, punctuation marks and those words with a high frequency of appearance, but of no significance to the essential semantic meaning and therefore to the objectives of the research, known as stopwords (Miner *et al.*, 2012).

3.3 Topic modelling – latent Dirichlet allocation (LDA) algorithm

The latent Dirichlet allocation (LDA) algorithm was used to identify topics from a collection of documents (Guo *et al.*, 2017), in a similar way to clustering methods for numeric data (Silge and Robinson, 2017). The underlying assumption of this model is that each document is a mixture of topics, and each topic follows a multinomial probability distribution over words (Blei *et al.*, 2003). The LDA model was estimated using the collapsed Gibbs sampling procedure, following the indications of Kwartler (2017). The optimal number of topics was previously determined using the "CaoJuan2009" indicator (Cao *et al.*, 2009), calculated for a range of topics established by the researcher. In addition, the LDA algorithm also estimated a matrix with the probabilities of each document referring to the different topics.

3.4 Sentiment analysis

Sentiment analysis, an area of Natural Language Processing (NLP), has as its objective the identification of emotions and their quantification (e.g. positive, neutral or negative), or the identification of a certain type of emotional state (e.g., happy, sad, or angry) in relation to a particular subject in a text document (Alaei *et al.*, 2019; Liu *et al.*, 2022). Three different techniques can be distinguished for sentiment analysis: (1) machine learning methods; (2) lexicon-based methods; and (3) hybrid methods (Alaei *et al.*, 2019; Liu *et al.*, 2022). Machine learning methods use algorithms where a model is trained with a data set of previously determined sentiments. After training the model, the algorithm predicts the sentiment of the

Authors	Data	Main purpose	Method	Major findings
Zhang *et al.* (2010)	1,242 online reviews from Dianping.com	To analyse the influence of online reviews on the popularity of restaurants	Regression analysis	Restaurant popularity was influenced by customer ratings of the quality of food, environment, service and the volume of online reviews
Pantelidis (2010)	2,471 online reviews from www.london-eating.co.uk	To identify the most important factors that constitute the restaurant experience	Content analysis	The main factors that customers evaluated in their restaurant experience were as follows: food, service, ambience, price, menu and decor (in that order)
Yan *et al.* (2015)	10,136 online reviews from Koubei website	To analyse the influence of online reviews on restaurant revisit intentions	Regression analysis	Restaurant customer revisit intentions were influenced by customer ratings of food quality, price and value, service quality and ambience
Kim *et al.* (2016)	Online reviews of more than 70 restaurants in 16 states in the USA from TripAdvisor, Urbanspoon and Foursquare	To analyse the influence of online reviews on the financial performance of restaurants	Hierarchical multiple regressions	Customer overall rating, guests served per working hour, customer rating of food quality and number of online reviews had a significant impact on restaurant performance
Gan *et al.* (2017)	268,442 online reviews of 7,508 restaurants from Yelp	To analyse the influence of online reviews on overall customer rating	Sentiment analysis Multilevel models	Sentiment toward food, service and context were the main attributes affecting overall customer rating, followed by sentiment toward price and ambience
Vu *et al.* (2019)	40,948 online reviews of 2,265 restaurants from TripAdvisor	To analyse the differences in online reviews between Western and Asian restaurant customers	Sentiment analysis of customer comments Z and chi-square tests	The Western group had significantly higher preferences for service, price and ambience than the Asian group

Table 1.
Empirical studies related to online restaurant reviews

(*continued*)

Authors	Data	Main purpose	Method	Major findings
Pezenka and Weismayer (2020)	100,831 online reviews of restaurants located in the city of Washington D.C. from TripAdvisor	To identify the most important factors linked to the restaurant experience To analyse differences between local and visitor customers To analyse the influence of factors on overall customer rating	Sentiment analysis of customer comments Mann–Whitney *U* test Linear regression	Restaurant experience attributes: drinks, facilities, food, business, menu, reservations, cleanliness, desserts, location, quietness, payment, ambience, value and staff Greater differences between locals and visitors for drinks and facilities Food was the attribute with the greatest influence on the overall customer rating
Mathayomchan and Taecharungroj (2020)	935,386 online reviews of 5,010 restaurants from Google	To analyse the influence of online reviews on overall customer ratings	Sentiment analysis of customer comments Logistic regression	Sentiment toward food is the most important attribute affecting overall customer ratings, followed by sentiment toward service, ambience and value
Luo and Xu (2021)	112,412 online reviews of American restaurants from Yelp	To identify the most important factors of the restaurant experience	Sentiment analysis of customer comments Various text-mining algorithms	Four major attributes were identified: service, food, place and experience
Nilashi *et al.* (2021)	6,342 online reviews of vegetarian restaurants in Bangkok from TripAdvisor	To develop a method for customer restaurant segmentation	LDA algorithm for text mining, SOM for data clustering and CART for preference prediction	LDA identified four dimensions: food, value, service and atmosphere Using these factors, four customers' segments were presented
Aktas-Polat and Polat (2021)	2,585 reviews on TripAdvisor for 46 five-star hotel restaurants in Istanbul	To discover the factors affecting customer delight, satisfaction and dissatisfaction in fine dining experiences	The latent Dirichlet allocation algorithm	The most important factors for customer delight, satisfaction and dissatisfaction were staff, view and food quality, respectively

(*continued*)

Table 1.

Authors	Data	Main purpose	Method	Major findings
Rita *et al.* (2023)	8,871 reviews on TripAdvisor of 87 restaurants in Europe	To investigate how sentiments toward food, service, ambience and price change after a restaurant is awarded a Michelin Star	Sentiment analysis of customer comments	Sentiments toward service, food and ambience decreased, while price sentiment showed a significant increase, after restaurants were awarded a Michelin Star

Table 1.

Source(s): The author's own work

	Online reviews	%
Number of stars		
One star (181 restaurants)	51,115	72.8
Two stars (32 restaurants)	10,451	14.9
Three stars (11 restaurants)	8,667	12.3
Total	70,233	100
Restaurant rating		
5 (25 restaurants)	6,378	9.1
4.5 (172 restaurants)	58,521	83.3
4 (24 restaurants)	4,755	6.8
3.5 (3 restaurants)	579	0.8
Total	70,233	100

Table 2.
Sample of online restaurant reviews

Source(s): The author's own work

other text documents. Lexicon-based methods use dictionaries of words classified into a set of predefined types of emotions with a sentiment score. In hybrid approaches, machine learning and lexicon-based approaches are used together to perform a sentiment analysis.

The main advantages of lexicon-based sentiment analysis are universality and easy practical implementation (Liu *et al.*, 2022). For these reasons, this paper to measure the polarity of the sentences of the online reviews, specifically, the AFINN-11 sentiment lexicon (Nielsen, 2011) (Spanish version). The sentiment score of the sentences was calculated by summing the ratings of the words that were cross-referenced with the AFINN-11 lexicon. And, following Gan *et al.* (2017), the sentiment score of each restaurant topic reflected the sum of the sentiment scores of the sentences, proportionally weighted by the number of sentences of each restaurant, as follows:

$$Sentiment\ score_{jk} = \frac{\sum_i \text{Sentiment score}_{ijk}}{\text{Nsentences of restaurant}_k}$$

where.

$i = 1 \ldots$ Nsentences of topic j in restaurant k

$j = 1 \ldots$ Ntopics.

$k = 1 \ldots$ Nrestaurants.

3.5 Logistic regression analysis

Finally, a multinomial logistic regression analysis using SPSS V.26 was performed to assess the influence of attributes on restaurant ratings. This linear regression model is recommended when the dependent variable is categorical with more than two values (e.g. ordinal or nominal scales), while the explanatory variables can be continuous or categorical (Peng *et al.*, 2002). Mathematically, the logistic regression model is expressed as:

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \sum_i \beta_i x_i$$

$$p = 1 + \frac{1}{e^{-\left(\beta_0 + \sum_i \beta_i x_i\right)}}$$

Where the independent variables (X_i) are the sentiment scores of the restaurant topics and p represents the estimated probability that a restaurant will either achieve a certain score or will not achieve that score, compared to the reference category previously fixed by the researcher. Multinomial logistic regression models assume that the effects of the explanatory variables may differ depending on the categories that are compared (Agresti, 2019). The comparisons between consecutive restaurant ratings will be shown following the proposals of Mathayomchan and Taecharungroj (2020).

4. Results

4.1 Topics of restaurant experience

Once the tokenization and cleaning process of the 70,233 online reviews was complete, a document-term matrix (DTM) was created with the entire corpus of sentences. Taking this matrix as an input, the CaoJuan2009 indicator was calculated for a range between 2 and 15 topics. The minimum value of this metric was reached in the solution of eight topics. In addition, as later shown in the estimation of the LDA model, this solution showed easily interpretable topics in semantic terms and with clearly different meanings, in line with the suggestion of Sievert and Shirley (2014).

The graphical visualisation of the model estimated with the LDA algorithm is shown in Figure 1. The topics are represented with circles on the left, while the words that are most related to each topic appear on the right. The topics are numbered according to their importance, which is determined by the size of the circles. The blue bars and the red bars indicate the total number of occurrences of that word in the entire set of online comments, and in each topic, respectively. In addition, the relevance metric was set at 0.6, to order the terms by their importance for each topic, following the indications of Sievert and Shirley (2014). The document-topic probabilities matrix was used to assign the sentences to the topics with a major probability. Approximately, 75% of the sentences were assigned with a probability greater than 0.7, which suggests that the algorithm classified the sentences among the topics with a relatively high power of discrimination. Finally, the researcher labelled and described the topics, using the most closely related words and the most likely content of the sentences in each one (Table 3).

4.2 Influence of attributes on restaurant ratings

The results of the logistic regression analysis showed a positive and statistically significant relationship between the restaurant ratings and the sentiment scores of the attributes of the restaurant experience (χ^2: 80.353; $p < 0.001$) (Table 4). Specifically, 4-star restaurants significantly increased their probability of achieving 4.5-star status by improving customer

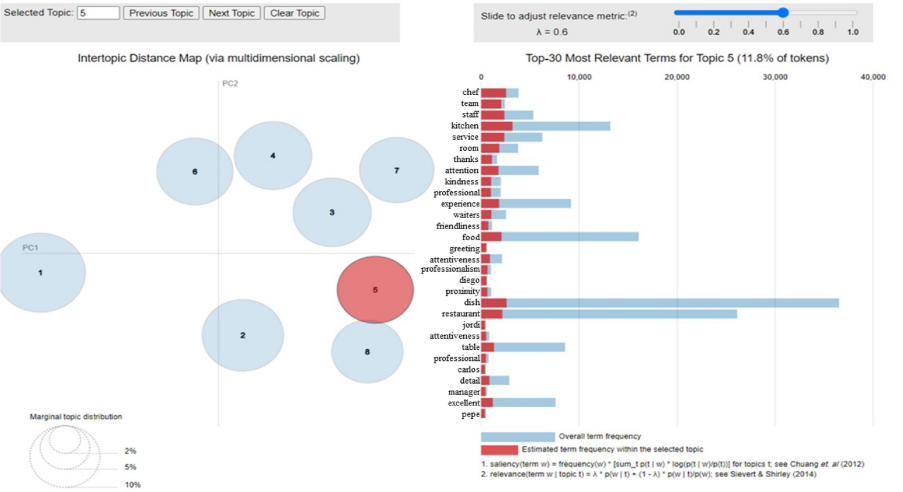

Figure 1.
Visualisation of the estimated LDA model

Source(s): The author's own work

attention (Wald's χ^2: 11.794; $p < 0.01$), food quality (Wald's χ^2: 6.222; $p < 0.05$) and tasting menus (Wald's χ^2: 4.673; $p < 0.05$). Similarly, sentiment score improvements with regard to customer attention (Wald's χ^2: 11.964; $p < 0.01$), wine pairing (Wald's χ^2: 6.409; $p < 0.05$), food quality (Wald's χ^2: 4.166; $p < 0.05$) and service failures (Wald's χ^2: 4.104; $p < 0.05$) implied significantly higher probabilities of a restaurant rating improving from 4.5 stars to 5 stars. No significant effects were observed for the rest of the attributes or the number of Michelin stars on restaurant ratings. The influence of attributes on the probability of a restaurant increasing its rating from 3.5 stars to 4 stars could not be estimated by SPSS since there were only three 3.5-star restaurants within the sample. However, the sentiment score for service failures was significantly more negative in 3.5-star restaurants (mean: −0.275) than in 4-star restaurants (mean: −0.057) (Student's *t*-test: −3.795; $p < 0.01$). There were no significant differences between the restaurants with these ratings for the other attributes. The model presented a good fit with an R^2 Nagelkerke of 0.459, indicating that 45.9% of the variation in the dependent variable was explained by the independent variables. Figure 2 shows the effect of each attribute on the estimated probability that a restaurant will be able to increase its rating from a previous level, eliminating the influence of all other attributes.

5. Conclusions and discussion of results

5.1 Conclusions

There is a broad consensus among researchers that four attributes related to restaurant experiences are worth highlighting: customer attention, food quality, decor and ambience and value for money. Past research has also used these attributes to define the luxury-restaurant experience, with the difference that consumer expectations toward their performance are higher (e.g. Yang and Matila, 2016). However, it has been shown in this study that the experience in Michelin-starred restaurants goes beyond the evaluation of those four attributes. These findings are possible due to the analysis of online customer reviews with text-mining methodologies, with which a much more complete overview of the restaurant experience can be obtained.

No	Latent topic and description	Relevant terms	Sample of most related customer reviews
1	Tasting menu Customer description and evaluation of the dishes included in the tasting menus	Dessert, rice, dish, flavour, foie, chocolate, egg, ice cream, cream, cheese, cod, sauce, tuna, hake, tartar, fish, meat, salad, truffle, tomato, mushrooms, lamb, apple, crispy, soup, shrimp, suckling pig, cooked, octopus and lobster	"We started with some carrots with a bowl of cheese and truffles (excellent), then potato chips with marinated mussels (stupendous), then lemon gelatin and curried cream of turron (surprising), followed by beef fillet tataki with olive oil caviar and hot paprika, after which an aioli sauce on potato and cuttle-fish that was very well prepared, then a chick-pea stew with a poached egg that was all quite splendid, followed by tuna in breadcrumb sauce, after which roast piglet cooked to perfection, continuing with a sort of melon sorbet and mint with pineapple and ice-cream granita (very refreshing), and we finished with a sweet chocolate mousse and groundnut ice-cream"
2	Food quality Customer evaluation of the visual presentation, creativity, flavours, textures, cooking techniques and quality of the products	Flavours, dish, product, cuisine, presentation, textures, quality, flavour, menu, material, raw, food, elaboration, excellent, elaborated, experience, surprising, ingredients, mix, palate, traditional, tasting, presentations, traditional, explosion, senses, combination, region, elaborations and technique	"It is really the best preparation of products from the Mediterranean area, treated with the greatest possible care, simplicity, and originality by professional Japanese cooks, known by all for the care that they take over the basic ingredients, respecting freshness and taste"
3	Value for money It reflects the overall assessment of the restaurant experience related to the price, customer satisfaction and future behavioural intentions	Price, star, quality, Michelin, restaurant, food, relationship, worth, menu, deserving, level, expensive, experience, dish, excellent, best, cheap, tasting, cuisine, high, product, category, treatment, recommendable, account, eat and attention	"A Michelin star restaurant where you can eat traditional food with well-prepared products (extensive and varied menu, with a section on traditional food with a touch of innovation), with servings that are so well balanced and a reasonable price, three difficult factors to find in star-rated restaurants; I am a little tired of restaurants with stars serving dishes with long names, for which you pay outlandish amounts and you are often left to go hungry"

(*continued*)

Table 3.
Identified attributes of the restaurant experience

No	Latent topic and description	Relevant terms	Sample of most related customer reviews
4	Service failures Related to common service restaurant failures such as reservations mistakes, poor telephone service, removal of plates or glasses from the table without consent, long waiting times between courses, errors with the bill, excessively long payment times, unfriendly attitudes and poor presentation of dishes	Table, dish, waiter, reservation, time, water, bread, detail, bill, menu, wine, minutes, problem, wrong, waiters, cup, order, diners, serve, waitress, eat, restaurant, bottle, coffee, people, wait, person, take, arrive and bad	"Awful, after visiting them year after year because of their good cuisine, I have to say that the customer care was no good, we had a reservation for 10 people and they made a mistake with the date, and we were expected to return another day, I am sad to say that their customer care is intolerable"
5	Customer attention Customer evaluation of the professionalism, education, kindness, and friendliness of the chef and the rest of the restaurant team	Chef, team, staff, kitchen, treatment, room, thanks, attention, friendly, professional, experience, waiters, friendliness, food, greet, attentive, professionalism, Diego, nearby, dish, restaurant, Jordi, attentive, table, professionals, Carlos, detail, boss, excellent and Pepe	"The care, professional approach and friendliness catch your attention in the first place, as it is not everywhere where that at once warm and exquisite atmosphere is evoked and it is all an achievement of the team that make up the restaurant, highlighting the management of the maître, whose name I am sorry I cannot recall right now, and lastly to highlight the guiding light of the restaurant, that is to say the cook who came into the dining room and walked around, table by table, interested in knowing our opinions on the evening meal"
6	Wine pairing Customer description and evaluation of the quality and variety of the wines offered by the restaurant to pair the dishes	Menu, wine, tasting, dish, pairing, menu, dessert, ordered, chose, long, short, Euros, price, drank, starters, red, taste, white, bottle, choice, sommelier, appetisers, person, glasses, cellar, cava and selection	"The wine pairing was to begin with a Rueda, white wine (Fenomenal 11- Happy grapes), quite good, followed by another white wine D.O Empordà (Cigonyes Blanc 11- Castell de Perelada), excellent, after which a red wine D.O Costers del Segre (Cérvoles Negre 06), also excellent and to end a Cava D.O Empordá (Stars Brut Nature 09 from Castell de Perelada), an excellent champagne"

Table 3. (*continued*)

No	Latent topic and description	Relevant terms	Sample of most related customer reviews
7	Context Related to previous expectations, dining purpose, companions, overall customer satisfaction and behavioural intentions	Restaurant, star, Michelin, experience, eat, expectations, friends, celebrate, visit, day, best, dine, couple, week, anniversary, Madrid, enjoy, birthday, go, visit, best, city, hotel, desire, high, Barcelona, months, return and days	"I had wanted to visit the Aponiente restaurant for some time, and I feared it might be a disappointment, having such high expectations, having visited some of the best restaurants of Spain (Can Roca, Akelarre, Diverxo, Quique Dacosta, etc . . .), but without a doubt the experience exceeded my expectations"
8	Decor and ambience Customer description and evaluation of the location, views of the restaurant, decoration of the different rooms (reception, dining room, rest room, toilets, *etc.*), dining room accessories (tables, chairs, cutlery, crockery, tablecloths, *etc.*) and ambience (temperature, sound and lighting)	Premises, decor, ambience, table, views, pleasant, restaurant, cosy, dining room, food, terrace, space, surroundings, quiet, staff, kitchen, treatment, price, elegant, attention, room, interior, decorated, beautiful, located, modern, entrance, bar, garden and building	"A very classic atmosphere and decoration (in the best sense of the word), with a fine carpet and beautiful ornamental plaster casts on the walls (damaged in some parts by the chairs scraping against the walls), with very comfortable velvet seats and, of course, fine silver-plated cutlery, which was changed with each dish"

Source(s): The author's own work

Table 3.

Dependent	Predictor	B	Std. Error	Wald's χ^2	Sig
4-star to 4.5-star rating	Intercept	−5.116	1.754	8.505	0.004**
	Tasting menu	5.070	2.345	4.673	0.031*
	Customer attention	9.508	2.769	11.794	0.001**
	Value for money	3.221	2.549	1.597	0.206
	Food quality	7.561	3.031	6.222	0.013*
	Wine pairing	−0.795	2.676	0.088	0.766
	Context	3.615	2.735	1.747	0.186
	Service failures	1.497	3.513	0.182	0.670
	Decor and ambiance	0.327	1.389	0.055	0.814
4.5-star to 5-star rating	Intercept	−6.247	1.979	9.967	0.002**
	Tasting Menu	−3.754	3.151	1.419	0.234
	Customer attention	5.856	1.693	11.964	0.001**
	Value	−1.470	3.314	0.197	0.657
	Food quality	5.322	2.607	4.166	0.041*
	Wine pairing	8.150	3.219	6.409	0.011*
	Context	−5.233	3.589	2.126	0.145
	Service failures	8.678	4.284	4.104	0.043*
	Decor and ambiance	−0.319	1.723	0.034	0.853

Note(s): *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$
Source(s): The author's own work

Table 4.
Results of the logistic regression analysis

Frequently, authors have stated that food quality is the main factor of a restaurant experience (Zhang *et al.*, 2010; Yan *et al.*, 2015; Kim *et al.*, 2015; Gan *et al.*, 2017; Pezenka and Weismayer, 2020; Mathayomchan and Taecharungroj, 2020; Kim and Hwang, 2022). In this paper, the

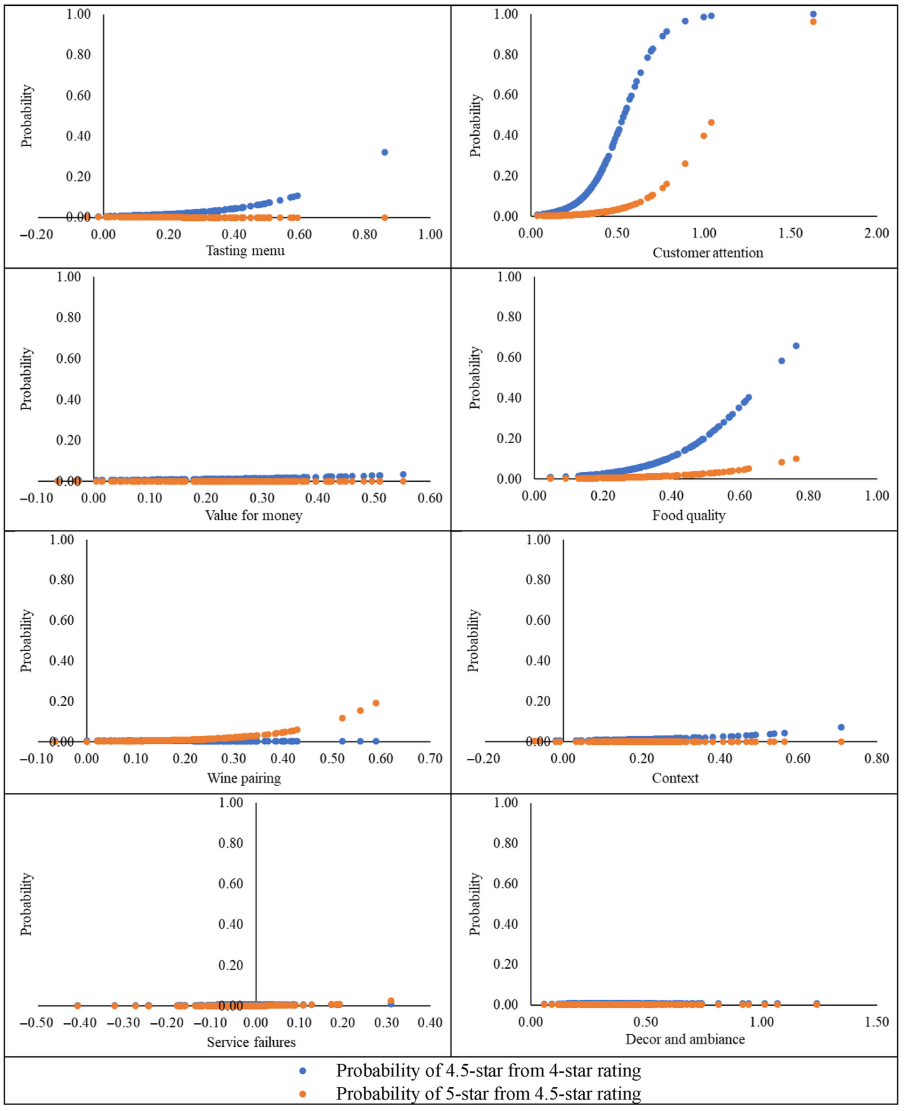

Figure 2.
Effect of attributes on restaurant ratings

Source(s): The author's own work

significant effect of food quality has also been demonstrated on restaurant ratings. However, in the specific context of Michelin-starred restaurants, the differences between customer ratings are mainly explained by customer attention. A finding that leads to the conclusion that the effect of the attributes can vary depending on the type of restaurant (luxury or non-luxury restaurant), as previously suggested by Mathayomchan and Taecharungroj (2020). Customer attention in dining experiences at Michelin-starred restaurants is also very relevant according to the study by Panchapakesan *et al.* (2022), who highlighted the role of service excellence in achieving consumer delight at luxury restaurants.

Researchers generally assume a linear relationship between attributes and customer satisfaction or restaurant performance (e.g. Zhang *et al.*, 2010; Yan *et al.*, 2015; Kim *et al.*, 2016). However, it has been suggested in this study that the effects of the attributes vary depending on the score of the restaurants. In other words, low-rating restaurants need to pay attention to certain factors and high-rating restaurants to other ones, in order to improve customer satisfaction.

5.2 Theoretical implications

Researchers have lent considerable attention to restaurant experience. Unfortunately, previous research on consumer experience in the context of Michelin-starred restaurants is limited. The contribution of this paper to the extant restaurant-experience literature is that the attributes evaluated by consumers during their dining experience in those restaurants have been identified. The findings confirm the presence of the four traditional factors of the restaurant experience: customer attention, food quality, decor and ambience and value for money. However, the Michelin-starred restaurant experience is more complex than has previously been suggested in the literature. Along with these attributes, the dishes that make up the tasting menus, including the products and ingredients used in their preparation, as well as the variety and quality of the wines offered to accompany the dishes are also described and evaluated by consumers. Possibly, its relevance is linked more to luxury restaurants than to other types of restaurants (e.g. fast food restaurants). The context of the dining experience was also found in the online reviews, showing the active role of the individual in creating the experience. Consumers narrated their previous expectations of dining at a Michelin-starred restaurant, the reason for the restaurant visit (e.g. a celebration of an anniversary or birthday, a business lunch, *etc.*), the companions (e.g. friends, partner or family), the global assessment of the experience and future behavioural intentions. Gan *et al.* (2017) pointed out that context reflects the personal and unique setting of the consumer experience in the restaurant. Finally, a dissatisfier attribute related to common restaurant service failures was identified. Theoretically, these findings share similarities to those of both Herzberg *et al.* (1959) and Crompton (2003), which suggested that consumer satisfaction is explained by motivator/satisfier and hygiene/dissatisfier attributes.

5.3 Methodological implications

From a methodological point of view, the use of online reviews as a source of data collection offers a more complete and realistic view of the restaurant experience, as it is based on opinions freely expressed by consumers. Consequently, the text-mining analysis of these online reviews offers the advantage of identifying attributes beyond those that traditionally make up the restaurant experience. On the contrary, researchers who make use of predetermined questionnaires for their empirical studies condition the identifying attributes of the restaurant in so far as they must appear in the questionnaires (Gan *et al.*, 2017). The results have also shown that research methodologies based on text mining analysis (e.g. topic modelling and sentiment analysis) are powerful tools for understanding consumer behaviour.

On the other hand, researchers often use linear regression analysis to test the effect of restaurant experience attributes on different dependent variables (e.g. Yan *et al.*, 2015; Pezenka and Weismayer, 2020). However, the logistic regression analysis is more appropriate given the categorical nature of the dependent variable (Mathayomchan and Taecharungroj, 2020; Wang *et al.*, 2023). In addition, this statistical analysis is also useful to determine whether the effects of the independent variables differ depending on the values of the dependent variable.

5.4 Practical implications

The findings of this research also have important implications for Michelin-starred restaurants. If customer satisfaction is to be improved, customer attention followed by food quality must be priorities. A positive evaluation of the professionalism, education, kindness and friendliness of the chef and the rest of the restaurant team will significantly increase the ratings of a restaurant. Likewise, restaurant managers should strive to improve creativity, the combination of flavours and textures, visual presentation and product quality used for the preparation of the dishes. Beyond the improvement of customer attention and food quality, restaurants increase their probability of achieving culinary excellence, symbolised in 5-star status, if they offer an error-free service and a highly appreciated wine list among diners.

In addition, restaurants with lower ratings should have as a priority objective the correction of service failures to increase customer satisfaction. Problems with reservations, poor telephone service, removal of plates or glasses from the table without consent, long waiting times between courses, errors with the bill, excessively long payment times, unfriendly attitudes and poor presentation of dishes are frequently mentioned in the online reviews related with this issue. The identification and correction of these service failures makes it possible to improve the experience offered to the consumer (Oviedo-García *et al.*, 2019). In addition, it is important to detect these errors during the provision of the service, so as to offer timely solutions before negative online reviews are generated (Kim and Hwang, 2022).

Finally, restaurant decoration was the attribute that consumers evaluated best of all. However, its influence on satisfaction was not significant. The results indicated that the attribute was positively evaluated both in restaurants with low and high ratings and its improvement never implied greater consumer satisfaction. Results that were in line with the research of Kim and Hwang (2022), who also found no significant effect of that attribute on consumer satisfaction.

Michelin-starred restaurants are also considered important tourist attractions (Castillo-Manzano *et al.*, 2021). Two basic lines are proposed from the perspective of destination tourism management. Firstly, the creation of culinary schools could not only contribute to achieving gastronomic excellence, but also to the development of tourist destinations. And, secondly, Michelin-starred restaurants and each destination management organisation (DMO) must jointly develop marketing strategies to promote tourist destinations with a reputation for excellence in gastronomy. The implementation of these actions will definitely be of benefit to both the tourism industry and gastronomy in general.

5.5 Limitations and future lines of research

In any research paper, the results obtained depend largely on the data sample collected. Specifically, the quality of samples based on online reviews can be negatively affected by grammatical mistakes, misspellings and jargon. On the other hand, domain-specific dictionaries can improve the results of sentiment analysis (Liu *et al.*, 2022). However, to the best of the author's knowledge, restaurant-specific sentiment dictionaries are as yet unavailable. It was also assumed in the study that the online reviews were based on truthful opinions. However, there is ample evidence that online manipulations occur to favour a company's own products or services and to harm competitors (Mellinas *et al.*, 2016). Finally, it is necessary to point out that the results of this research are circumscribed within the context of Spanish restaurants with Michelin stars. Future research should be developed with restaurants from other countries using opinions written in other languages that may either refute or uphold the conclusions of this study.

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