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FROM BOOKING TO RATING ACTIVITIES: A HOLISTIC ANALYSIS OF ONLINE REVIEW BEHAVIOR IN A DESTINATION

Abstract

The objective of this study is to analyze the online review behavior of users in the context of a range of activities undertaken at a destination while considering the determinant factors at three stages, namely, reservation (booking time and price), consumption (experience), and post-consumption (online behavior). Drawing on expectancy–value theory and cognitive dissonance theory, the main contribution of this paper to the tourism literature lies in its argument that the timing of the characteristics that describe the above activities may have different effects on the final response of users, be it their qualitative decision of posting or their quantitative decision of rating. By taking advantage of a unique database containing information at different stages from booking to rating, results show that the prices, which are observed at the booking time, can affect the posting and rating decisions of users, while the moment of the activity, which is observed at the consumption stage, only affects their posting decision.

Keywords: online ratings; online reviews; Heckit models; booking; price; booking time

1 Introduction

Online reviews can affect online platform users' decisions in several areas, such as hotels (Kim & Kim, 2022), travel companies (Rita et al., 2022), restaurants (Li et al., 2019; Rita et al., 2023), and destinations (Calderón-Fajardo et al., 2024; Schoner-Schatz et al., 2021; Su et al., 2022). While previous studies have made valuable contributions to online review behavior research, they fail to connect (i) the booking variables and (ii) tourist activities within a trip to the posting and rating decisions of users. Previous studies on online reviews have also failed to integrate crucial booking variables, such as the tourism activity's price and the interval between the experience and the posting time. Although a large number of studies have explored the effects of booking prices and timing (see Bigne et al., 2021 for a review), studies on their relationships with posting online reviews in subsequent trip activities are scarce, with notable exceptions (Kim & Kim, 2022; Ye et al., 2023).

This study adopts the trip and its related tourist activities as a core research topic by addressing online review behavior conditioned by the price of those activities and the time when bookings were made. Our holistic perspective differs from previous research that focuses on only one activity (e.g., restaurants) and neglects the relationship between posting behavior with booking price and time of the booking. A trip is a multifaceted activity that involves different activities. The posting behavior of users, especially the relationship between their trip (and the activities involved) and online review behavior, warrants further research. Most of the activities involved in a trip, such as tours, visiting monuments, and eating at restaurants, take place in a tourism destination. Those studies that only focus on a single activity (e.g., eating at a restaurant) may not be able to highlight the relationship between users' online review behavior and their entire trip experiences. Therefore, we aim to fill the aforementioned three research gaps that drive our research questions: (i) by relating posting behavior to the time elapsed between booking and experience, we investigate (RQ1) whether time elapsed has any influence on online posting behavior, and (ii) by relating online posting behavior to a financial variable (i.e., money paid), we address (RQ2) whether the amount paid influences online posting behavior, and (iii) by integrating users' online ratings of the activities involved in a trip, we address (RQ3) online posting behavior by activity type. Figure 1 illustrates our research framework, and its details will be shown in the next section.

Figure 1 around here

Online behavior analysis based on large datasets is becoming increasingly popular following the advent of big data and data analytics. Although a few studies have explored users' digital trajectories or footprints by integrating various datasets (Salas-Olmedo et al., 2018), no previous study has used a single-source dataset that covers all activities conducted during a trip. Contrary to the dominating practice in the literature, in this study, we examine the temporal closeness between travel experience and a review's posting time from the uploader's point of view than from the users' perspective (Li et al., 2020).

Research on posting about activities in a destination may provide relevant avenues for (i) understanding the drivers of posting and rating behavior during a trip; (ii) analyzing the decision to post and rate activities instead of the facilities that have been traditionally examined at the individual level, such as accommodation and restaurants; and (iii) adopting a longitudinal analysis that integrates posting activity with booking variables, such as the price of a tourism activity or the time lag between the experience and the posting.

By taking booking price into consideration, learning about the types of posts shared by users during the entire trip and during their activities can contribute novel insights into their posting motives with an integrative perspective. In this sense, data from travel agencies provide a unique framework that uses a longitudinal view and a series of tourist activities linked with booking characteristics (e.g., price).

Given that users post online reviews from different countries and use different languages, we also explore, as RQ4 and RQ5, respectively, whether the country of origin and language of these users affect their decision to post and the content of their posts.

Building upon the experience economy paradigm (Pine & Gilmore, 1999), we analyze how the posting and rating decisions of users are affected by their types of experiences (activity type and time variables) and the price of their bookings. Given that users' perceptions about price value evolve over time, it is interesting to test how the time lag between a booking and the experienced activity shapes their posting and rating decisions. This time lag may affect such decisions due to the perceived financial effort.

The objective of our research is twofold. First, we explore the links between users' booking variables, such as price and timing, and their online review behavior by adopting their trip as a research framework. Second, using an integrative approach, we analyze the posting and rating behavior of users based on their activities during their trip. The granularity of our dataset from a travel agency allows us to integrate posting activities with certain variables, such as booking price, the time passed between the booking and the activity, and the time passed between the activity and the posting of an online review.

To the best of our knowledge, no previous research has had access to a database that fully tracks users' activities from their booking of a tourism service to their assignment of a rating. Our database records all available purchases of users and the ratings and reviews that correspond to these purchases.

Our work contributes to the literature in several ways. First, our findings provide explanatory variables that aid in understanding how users behave differently in their rating decisions (whether to give a rating or not) and their rating levels based on four critical variables, namely, the booking price, the number of days passed between the activity and the assignment of rating, the nationality of users, and the number of adults and children participating in the activity. Second, our decision to analyze multiple tourism activities can provide a richer explanation of users' posting and rating behavior and the types of comments that they have made during their trip but are related to other services.

2 Literature review

2.1 Social media reviews and booking

In a digitally connected world, online reviews play a pivotal role in consumer decision-making. Some of the issues that have been extensively researched regarding online reviews are how helpful they are (Filieri & Mariani, 2021; Lee et al., 2021), their credibility (Lopes et al., 2021; Pooja & Upadhyaya, 2022), and their impact on booking intentions (Sparks & Browning, 2011). These online reviews are particularly important in the hotel and hospitality industry. When consumers contemplate on booking a specific service, a series of factors come into play. Many studies have explored the multifaceted impact of online reviews on consumer choices (e.g., Wen et al., 2021; Zeng et al., 2020; Zhao et al., 2015). Online reviews have become a critical resource for consumers in their quest for the perfect hotel or hospitality experience.

The overall rating of a hotel, which is calculated as the average of all reviewers' ratings accumulated over time, summarizes the collective sentiment expressed in individual textual reviews. Therefore, this rating is a crucial indicator for prospective guests to quickly assess the overall quality of a property. Furthermore, a significant distinction can be observed between extremely positive and extremely negative reviews. While extremely positive reviews may be perceived as less meaningful, lower-rated reviews with crucial informational cues can be highly influential (Bridges & Vásquez, 2018). Lo and Lin (2017) explored the relationship between deal evaluations and electronic word-of-mouth intention and found that consumers' evaluations of deals, which are influenced by their previous exposure to prices and their social connections, can carry over to their electronic word-of-mouth intention. This effect is as powerful as that of reference prices.

Given the experiential nature and high uncertainty associated with hotel products, consumers tend to place greater emphasis on the content and associated sentiment in online reviews within the hospitality context (Bigne et al., 2021; Mirzaalian & Halpenny, 2021; Nicolau et al., 2024). Understanding the real experiences of previous guests plays a pivotal role in the decision-making process of prospective customers. This dynamic approach acknowledges that a hotel's performance may fluctuate, thereby making recent reviews more indicative of its current situation.

However, the content of online reviews is not homogeneous given the presence of several critical components, with each component contributing to the overall impression formed by the reader. These components include linguistic characteristics, temporal dimension, cultural context, content, sentiment, individual ratings, peripheral cues, and reader feedback (Albayrak et al., 2021; Liang et al., 2021; Xiang et al., 2017). These multidimensional elements collectively influence the consumer's perception of the informational value of a review.

The linguistic characteristics of a review, such as its length and readability, impact its perceived usefulness (Park & Nicolau, 2015). The textual content of a review provides insights into the reviewer's direct experience with various attributes of the hotel, thereby allowing prospective guests to gauge the quality of their potential experience. Drawing on regulatory focus and construal level theory, Kim and Kim (2022) found that consumers evaluate hotel reviews differently based on their temporal orientation and regulatory focus. Temporal distance moderates the impact of regulatory-focused reviews, with future-oriented consumers showing more positive attitudes when reading promotion-focused reviews. Shin et al. (2017) employed construal-level theory to explore the effect of online travel reviews on tourists' perceptions and found that the temporal dimension of psychological distance significantly influences the usefulness of travel reviews. While concrete reviews tend to have a greater impact on users whose travel dates are drawing near, abstract reviews tend to attract those users who are intending to travel in the distant future. Yang and Han (2022) explored the impact of mobile device usage and temporal distance on consumers' post-consumption evaluations, encompassing review ratings and text sentiments. They found that mobile device usage has a significantly negative direct impact on consumers' evaluations, whereas temporal distance exerts a positive effect, thus mitigating the negative relationship between mobile device usage and evaluations.

Consumers also use the reviewers' personal information as a measure of their review's authenticity and trustworthiness (Park et al., 2015). Knowing more about the reviewer's background and context can significantly affect the credibility of his/her review. The motives of reviewers are equally important. Hennig-Thurau et al. (2004) highlighted that consumer motives play a significant role in driving online articulation. Motives, such as the desire for social interaction, economic incentives, concern for other consumers, and the potential to enhance one's self-worth, are primary factors leading to electronic word-of-mouth behavior.

Consumer reliance on electronic word-of-mouth extends beyond the hotel industry. Electronic word-of-mouth is also prevalent in other hospitality services, such as restaurants. Jeong and Jang (2011) examined the relationship between restaurant experiences and positive electronic word-of-mouth and found that the quality of a restaurant, including its food quality, service quality, atmosphere, and price fairness, significantly influence customers' willingness to engage in positive electronic word-of-mouth. A superior atmosphere in restaurants and satisfactory experiences with service employees are particularly useful in encouraging positive electronic word-of-mouth, thus reflecting consumers' concern for others. Li et al. (2019) investigated the social influence on restaurant evaluation and found that a restaurant's prior average review rating and number of prior reviews significantly influence consumers' evaluations. The temporal distance of reviews also has a direct negative effect on restaurant evaluation, thereby emphasizing the importance of recency. Beyond hotels and restaurants, Bronner and De Hoog (2011) explored the dynamics of electronic word-of-mouth in the vacation industry. These authors examined the motivations behind consumers' posting of reviews regardless of the site. Motivational factors play a crucial role in shaping the types of contributions of these users, with a distinction between self-directed and others-directed motivations.

In summary, previous studies have largely confirmed the impact of electronic word-of-mouth on booking intentions and purchase behavior. While this effect can be found in almost any industry, it is particularly relevant in tourism (Chu et al., 2020) due to two main characteristics of tourism products: the time that elapses between booking and consumption and their intangible nature. While research initially focused on the average rating and demonstrated its relevance, interest subsequently shifted to other specific characteristics of the reviews, such as their valence, review timeliness, length, and readability. In conclusion, while there is agreement on the impact of online reviews on customer decision-making, research has shown that this impact is highly variable and depends on many factors. The literature has addressed those factors, including users' sentiment (Zhang et al., 2024), higher record valences relate to satisfaction with subsequent bookings (Ye et al., 2023), adverse effects of closer transactions and guest satisfaction (Zhang, et al., 2021), the local people tend to psot high quality reviews (Liang, et al., 2022). However, most studies have ignored the interactions between trip-related booking variables (e.g., price paid and booking anticipation) and posting behavior. To fill this gap, we focus on users' posting and rating behavior throughout their entire trip. Understanding the relationship between trip bookings and posting behavior can provide valuable insights into consumer behavior in the tourism industry, in general, and for destinations, in particular. By focusing on the posting and rating behavior of users throughout their entire trip, we can gain a better understanding of how different factors influence their online engagement and, potentially, their decision-making process. This understanding can be crucial for businesses and destination marketing organizations in tailoring their strategies to meet the needs and preferences of travelers effectively.

Previous studies have investigated three areas, namely, motivation to post (Liang et al., 2022), rating score (Liang et al., 2022), and types of comments (Liang et al., 2020). Despite the high volume of studies on online comments, including meta-analyses and bibliometric studies (Babić Rosario et al., 2020; Chu et al., 2020), only a few scholars have performed an integrative investigation of online reviews while considering the different types of tourist activities conducted during a trip. Integrative studies are critical in further understanding the relationships between the cause (i.e., trip) and the behavior (i.e., post). We argue that the key variables of a trip may affect users' posting behavior. Such an integrative view is difficult to implement using archival data sourced from a single vendor because users may purchase activities from different vendors and providers during their trip. However, online travel agencies (OTAs) may provide a unique integrative framework for tracking these users' bookings during their trip, their activities in the destination, and their posting behavior at the individual level.

Nevertheless, no previous study has investigated the issues of online booking through OTAs and posting behavior simultaneously. Booking through OTAs constitutes a unique framework for tracking booking variables, such as the amount paid, time of booking, and number of users involved in the booking. The moment of experiencing a service may also influence the posting and rating decisions of users. Zhang et al. (2022) found that weather conditions affect users' online review posting behavior.

Studying these two aspects together provides a more comprehensive understanding of consumer behavior in the context of online travel, leading to an exploration of how online booking decisions interact with subsequent posting behavior and vice versa.

From a theoretical perspective, simultaneous investigation of these phenomena contributes to the body of knowledge in tourism and consumer behavior by filling the aforementioned gap. Moreover, understanding the relationship between online booking and posting behavior has critical practical implications for destinations as it can inform marketing strategies, customer engagement initiatives, and product development efforts aimed at enhancing the overall customer experience.

We then investigate whether booking variables affect the posting behavior of users in two directions, namely, their decision to post and the types of their ratings and comments. We propose the following research questions:

> RQ1: How do (a) time variables (booking anticipation and time to review), (b) booking variables (price), and (c) time of day when the activity took place affect posting behavior?
>
> RQ2: How do (a) time variables (booking anticipation and time to review), (b) booking variables (price), and (c) time of day when the activity took place affect rating behavior?

We formulate our research questions for anticipation and price based on expectancy–value theory (Eccles, 1983; Eccles & Wigfield, 2002) and cognitive dissonance theory (Festinger, 1957).

Expectancy–value theory (Eccles, 1983; Eccles & Wigfield, 2002) suggests that decisions related to achievement are driven by a combination of individuals’ anticipation for success and their personal assessment of the significance of a task in specific areas. Specifically, expectancy refers to an individual’s belief about the likelihood of a specific outcome resulting from a behavior. In our case, a high anticipation of a trip can lead to certain expectations. Users may anticipate that their trip will be exciting, enjoyable, and memorable, and this positive expectation can increase their likelihood of posting an online review. Meanwhile, value pertains to the importance or desirability of an outcome. When consumers anticipate a trip with high excitement, they tend to place a high value on their experience and the memories they will create. Such increased value attached to the trip experience can influence their motivation to engage in behavioral aspects related to the trip, such as posting an online review. They regard the act of reviewing as a way of capturing and preserving the value that they place on their experience. Given that expectancy–value theory posits that motivation to perform a behavior is determined by expectancy and value, the expectancy of having a positive experience during the trip and the value attached to the trip experience itself would motivate users to post an online review. In essence, they believe that sharing their positive experiences through a review will lead to a desirable outcome, such as reliving their memories, influencing others, or receiving social validation and recognition.

In other words, when people look forward to a trip, they often invest time and emotional energy in planning and anticipating such trip, and this emotional investment can increase their desire to share their experiences and feelings about the trip through an online review (Köchling & Lohmann, 2022). Moreover, anticipating a trip can lead to better memory retention of the trip's details as people may remember more vividly and provide a more comprehensive and detailed review if they are highly anticipatory before their trip (Skavronskaya et al., 2020). Therefore, if their actual experience matches or exceeds these expectations, then users may be motivated to express their satisfaction and share their positive experiences through reviews, which is in line with the arguments of expectancy–value theory (Eccles, 1983). Similarly, if users have high anticipation for a trip but their actual experience falls short of their expectations, then they may be inclined to post a review to express their disappointment or dissatisfaction as a way to resolve their cognitive dissonance.

To explain this dissatisfaction and the individual's motivation to post, we apply cognitive dissonance theory (Festinger, 1957), which focuses on the discomfort that people experience when they hold conflicting beliefs or attitudes and how they seek to resolve this dissonance. In the context of this study, when users are highly anticipatory about a trip, they tend to have certain expectations and positive beliefs about their upcoming experience. They may envision the trip as exciting, enjoyable, and memorable, thus building with strong positive expectations. This positive anticipation creates a specific cognitive state because these users hold positive beliefs and attitudes about their trip. If their actual trip experience aligns with or exceeds their positive expectations, then they observe a congruence between their pre-trip beliefs and post-trip reality. In such cases, they may experience minimal cognitive dissonance because their beliefs and attitudes have been confirmed by their actual experience. Given that cognitive dissonance theory proposes that people engage in self-justification to maintain consistency in their beliefs and actions (Goethals, 1992), posting a positive online review can serve as a form of self-justification, confirming to themselves and others that their high anticipation has been justified and that they have made a good choice in booking their trip. People often seek social validation for their decisions and experiences (Hillman et al., 2023), and by posting a positive review, they can receive external validation from their social networks, thus further reducing their cognitive dissonance. In other words, the positive reactions of others to their review may reinforce users' belief that they have made the right decision in booking their trip.

We provide analogous arguments regarding the relationship between prices and the probability of users to post an online review. According to expectancy–value theory, when users invest a significant amount of money in a trip, they typically hold high expectations, and this positive expectancy should motivate them to post a review. Moreover, when a trip is costly, users perceive this trip as a valuable experience. They may feel that the price they have paid represents a significant investment, and consequently, they ascribe a higher value to their trip. Therefore, posting a review serves as a way for these users to express and affirm the value they associate with their experience. In line with this theory, those users who have high expectancy and high value for their expensive trips are more motivated to post a review. They think of this review as their way to communicate the value they have received and the alignment between their expectations and actual experience.

In the context of cognitive dissonance theory, if the actual experience of an expensive trip meets or exceeds users' positive expectations, then they enter a state of cognitive consonance. In other words, these users find alignment between their pre-trip beliefs (expecting a premium experience due to the high cost) and post-trip reality (experiencing a premium trip). However, in case of any discrepancies between their expectations and the reality of their trip, these users may experience cognitive dissonance, and posting an online review can serve as a mechanism for them to reduce such dissonance. The same principles of self-justification and social validation also apply to price (Goethals, 1992; Hillman et al., 2023). Posting an online review can serve as a form of self-justification where users confirm to themselves and others that their financial investment is justified and that they have made a good decision in booking an expensive trip. These reviews may also gain them social validation from their peers and the broader online community.

2.2 Activities in the destination

Activities are a relevant component of any tourism destination and are among the six *As* that create a competitive destination together with attractions, accessibility, amenities, available packages, and ancillary services (Buhalis, 2000). Activities are also present in another popular model (Ritchie & Crouch, 2003), which claims that the combination of activities, special events, and entertainment is among the core resources and attractors of a destination.

Activities in the destination are a source of pleasure (Masiero & Nicolau, 2012), and researchers have analyzed which activities are most popular for each tourist segment, such as millennials (Rita et al., 2019) or seniors (Littrell et al., 2004). Therefore, as elements that bring about pleasure, we expect that activities affect the online behavior of users. Along this line, given every type of activity possesses its idiosyncratic characteristics, we explore whether they have distinct effects on the dimensions of interest. Specifically, we then propose the following research question:

> RQ3. Does the type of activity influence users' (a) decision to rate and (b) their rating?

2.3 Importance of the country of origin in online rating behavior

Country of origin is a main tourist segmentation variable (Legohérel et al., 2015). Several studies showed that tourists of various nationalities show different behaviors (e.g., Kozak, 2002; Park et al., 2015). Specifically, the culture of each nationality affects their posting and rating decisions (see Mariani et al., 2020 for a review). While these studies have focused on specific types of tourism resources, such as accommodation, airlines, or destinations, they have ignored the activities of tourists during their trip. Despite language being strongly linked to culture, the languages spoken by tourists may affect their types of comments (Schuckert et al., 2015) due to their limited linguistic knowledge or cognitive background in their mother tongue. Therefore, language is a useful complement to the country of origin for testing the types of comments. We then derive the following research questions:

> RQ4: Does the country of origin of tourists affect their (a) posting and (b) rating decisions?
>
> RQ5: Does the language in which a rating is posted affect the type of comments?

3 Dataset

In 2017, the travel agency Viajes Insular S.A. in Canary Islands, Spain launched its new business unit called Vimotions. The Canary Islands are a leading non-seasonal destination, attracting more than 15 million tourists in 2019, with just over 2 million inhabitants. The Canary Islands include eight islands, each with unique characteristics and a wide range of offerings. The islands receive tourists from a wide of countries, with more than 15 European countries as relevant origin markets. These 15 countries include a variety of nationalities with significant differences between them. For these reasons, the Canary Islands can be considered as reliable sample of vacation tourism behaviors. Viajes Insular is the main tourist distribution group in the Canary Islands that operates in seven of its eight islands. The Vimotions business unit was specifically created to post activity offerings in several OTAs, such as GetYourGuide, Viator, Expedia, and Atrapalo. Some of these OTAs are specifically focused on activities (e.g., GetYourGuide and Viator), while the others are general-purpose OTAs that offer different travel services (e.g., Expedia, which specializes in air tickets, hotels, transfers, and many other services). Before the launch of Vimotions, activities in Canary Islands were not yet being offered in any OTA, although some activities were available on the websites of those companies that offer such activities. The Vimotions database stores data on each booking made through the agency, including the number of reviews received by each attraction. Our database includes data on sales that took place in GetYourGuide. This OTA was selected as it keeps track of the users' history starting from their booking to their assignment of a rating (if a rating was given).

Our study covers a period of 18 months, starting from July 2017 (when Vimotions made its first sale) to December 2018, during which a total of 3,421 bookings were made through GetYourGuide. After excluding the canceled bookings, our final cross-sectional dataset comprises 3,047 sales and 759 online ratings (i.e., 24.91% of the bookings were rated).

For each booking, we obtained information on the booking date and time, the scheduled date and time of the booked service, the user's country of origin, the booked activity, the number of adults and children, and the total booking price. We classified each activity based the suggestions of experts. For each review, we obtained information on the reviewed booking, the review posting date, the numeric rating (1–5), and an optional text (the review). Based on these data, we calculated how far in advance the booking was made, including the days that passed from when the activity was completed to when the review was posted.

4 Methodology

We used Heckit models to examine the determinants of activity ratings (Heckman, 1976). Unlike classical regression models, Heckit models control for a potential sample selection bias by analyzing a user's decision to post a review before rating an activity. Sample selection bias can bring about spurious results and thus needs to be controlled.

Our empirical application may be affected by such bias because the rating given by users to a specific activity is only observed if these users have previously decided to post a review. Evidently, we cannot observe the ratings of those users who decided not to post a review. Users who post reviews might have different characteristics or motivations compared to those who do not. For instance, users with extreme opinions (very positive or very negative) are more likely to post reviews (Hu et al., 2009). This non-random selection can lead to biased estimates if not properly accounted for. Consequently, the available sample of ratings may not be representative of the entire population of users, potentially distorting the analysis and leading to spurious conclusions if standard regression methods are used.

The Heckit model addresses these biases through a two-step estimation process. First, the selection equation models the probability of a user deciding to post a review. By estimating this probability, we can understand the factors influencing the decision to review. Second, the outcome equation models the ratings given by users, incorporating the inverse Mills ratio derived from the first stage to correct for the sample selection bias. This correction ensures that the estimates of the determinants of activity ratings are unbiased and consistent.

Therefore, while controlling for sample selection bias, the Heckit model also facilitates the identification of determinants, if any, that may influence users' decision to post a review. In other words, we are dealing with quantitative (the rating given to activities) and qualitative decisions (whether to post a review). By using the Heckit model, we can account for the inherent sample selection bias present in our data, ensuring that our findings are robust and reliable.

We captured the decision to post a review about an activity by individual *i* using the latent variable DPR_i^*, which is explained by a set of independent variables, namely, "price" (Pr_i), "number of participants" (NP_i), "days in advance of purchase" (DAP_i), "time passed from the activity to the review" (TP_i), "time of the day in which the activity took place" (morning (M_i) and afternoon (A_i)), "whether the activity took place on the weekend" (W_i), type of activity ("ticket sales" (TS_i), "excursions" (E_i), and "other types of activities" (O_i)), and country k of the user who made the booking and left a review (C_{ki}). The β parameters reflect the influence of these determinants on the users' decision to post a review.

When analyzing the determinants of ratings R_i, we used the same independent variables as in the previous decision. However, we left out country in our analysis because in order to estimate the Heckit model, we must comply with its exclusion restrictions. In other words, a significant variable must enter Eq. (1) only (Heckman, 1976). The λ parameters show the impact of these variables on the rating.

Equation 1

$$DPR_i^* = \beta_1 + \beta_2 \cdot Pr_i + \beta_3 \cdot NP_i + \beta_4 \cdot DAP_i + \beta_5 \cdot TP_i + \beta_6 \cdot M_i + \beta_7 \cdot A_i + \beta_8 \cdot W_i + \beta_9 \cdot TS_i + \beta_{10} \cdot E_i + \beta_{11} \cdot O_i + \sum_{k=1}^{K} \beta_{11+k} \cdot C_{ki} + u_i.$$

Equation 2

$$R_i = \lambda_1 + \lambda_2 \cdot Pr_i + \lambda_3 \cdot NP_i + \lambda_4 \cdot DAP_i + \lambda_5 \cdot TP_i + \lambda_6 \cdot M_i + \lambda_7 \cdot A_i + \lambda_8 \cdot W_i + \lambda_9 \cdot TS_i + \lambda_{10} \cdot E_i + \lambda_{11} \cdot O_i + \varepsilon_i.$$

R_i in Eq. (2) is observed only if $DPR_i^* > 0$.

We assumed a bivariate normal distribution for the random terms u_i and $□_i$, whose mean is expected to be zero, and for the standard deviations $□_u$ and $□_□$, with covariance $□_{□u}$. We created a binomial variable DPR_i that equals 1 if the latent variable $DPR_i^* > 0$ and equals 0 otherwise.

Users' comments provide a valuable source of information about the types of content that they post during their trip. We then performed an exploratory processing of the review associated with a rating. We used Kamakura's Analytic Tools for Excel (KATE) (Kamakura, n.d.), specifically WordMap, and analyzed the comments separately in Spanish and English. These two languages represent the majority of the comments.

5 Results

5.1 Decision to post and rate

Table 1 presents the results of the two-step Heckit model where the determinants of the decisions to post a review and leave a rating are shown. Model 1 includes the total price, while Model 2 incorporates the price per person.

The response equation measures the impact of the variables on the rating, while the selection equation measures the impact of the variables on the decision to post a review. Thus, Models 1 and 2 show not only the variables that affect the rating but also those that affect the decision to post a review. Some variables influence the users' decision to post a review. The anticipation with which the booking was made exerts a positive impact, where a greater anticipation corresponds to a higher chance of posting a review. Given that we apply a log transformation to this variable to capture non-linear effects, the results show diminishing returns, where the incremental impact decreases with more days in advance, which can be seen in the graph depicted in Figure 2. However, this anticipation does not affect the rating. Price also has a significant effect, where a higher price corresponds to a higher chance of posting a review. We obtained the same result when considering the total price (Model 1) or the price per ticket (Model 2). Activities that take place on weekends have a lower chance of being rated. Moreover, users from specific countries have a higher predisposition to rate. Price has an influence on rating, with a higher price corresponding to a higher rating. This result is consistent with those for total price and price per ticket. The types of activities considered in this paper do not have a significant impact.

Figure 2 around here

Some variables are not significant in any of our models. These variables include the presence of children in the group, the time of day during which the activity takes place (morning or afternoon), and the days that passed between the activity taking place and the review being posted. We grouped these types of activities into ticket sales (e.g., entrance to a theme park), excursions (e.g., half day tour around a destination), and other types of activities (e.g., scuba diving and paragliding). Results show that these types of activities do not influence either the decision to post or the rating that is posted.

The rho parameter (ρ) is significant in Models 1 and 2, thereby suggesting that Eqs. (1) and (2) are correlated. In other words, sample selection bias poses an issue in our empirical application, and our use of the Heckit model is justified because it considers such bias when estimating the parameters.

Table 1 around here

For robustness checks, we estimated different model specifications. Specifically, instead of the log transformation of the variable "anticipation", Models 3 and 4 in Table 2 show basic linear specifications corresponding to Models 1 and 2 in Table 1, and Models 5 and 6 present specifications with quadratic terms. The results show robust findings because all the significant parameters in Table 1 remain significant in Table 2, with the exception of the variable “anticipation.” This highlights the superiority of the log transformation. The variable “anticipation” is not only significant in Table 1 but also leads the models to achieve the optimal specification according to the Akaike and Schwarz information criteria.

Tables 2 and 3 around here

5.2 WordMap processing

To complement the previous analysis and further understand the main elements in the reviews that accompany the ratings, we analyzed the reviews given by users via the WordMap tool in KATE (https://www.katexcel.com/home). However, including a review with a rating was optional. Thus, only 369 of the ratings had an accompanying review. These reviews were written in several languages, and we only processed those in Spanish (76 reviews or 20.60% of all reviews), English (86 reviews or 23.31%), and German (120 reviews or 32.5%). The comments in the three languages together accounted for 76.4% of the total text reviews, representing the largest proportion of reviews in any single language. Comments in other languages were relatively sparse and, therefore, excluded from the analysis due to their lower frequency and the potentially associated challenges of accurate processing. In processing the Spanish comments, after creating the final graphs using WordMap, we translated the words into English to make them understandable to a larger audience. By focusing on comments in Spanish, English, and German, we ensured a rigorous and precise qualitative analysis while still capturing a significant majority of the available textual data.

Figures 3a and 3b show the results of processing the Spanish reviews. We compared the ratings with the reviews to check whether bad ratings (a rating of 1 or 2) are associated with some specific words. In this way, we could understand the reason behind the dissatisfaction of the reviewer. Results in Figure 3b confirm that the activities with a lower rating do not show a certain pattern on the map. Notably, the cases of unsatisfied users were not very frequent (8% of the total).

Figure 3a shows that the two axes of the WordMap tool are oriented to two dimensions. The horizontal ax is oriented to animals, while the vertical ax references the enjoyment of the activity and the price.

Figures 3a and 3b around here

Figures 4a and 4b show the results of processing the English reviews. The ratings do not seem to follow a specific pattern and are not aligned over one of the axes. In the WordMap analysis (Figure 4a), the two axes are oriented to those items that are part of the activity (horizontal axis) and the feelings associated with the activity (vertical axis).

Figures 4a and 4b around here

Figures 5a and 5b show the results of processing the German reviews. The ratings do not seem to follow a specific pattern and are not aligned along any particular axis. In the WordMap analysis (Figure 5a), the two axes follow a similar pattern, which is oriented to those items that are part of the activity (horizontal axis) and the feelings associated with the activity (vertical axis). The comments across the three languages display a similar pattern, showing generic words with high frequency (e.g., tours, guide) and with positive adjectives (e.g., nice, great) and some specific activities (e.g., whales, dolphin, or diving) with fewer mentions further from the rest.

Figures 5a and 5b around here

6 Discussion

The results can be grouped into two main areas, namely, the variables that affect the decision to rate (RQ1) and the variables that affect the rating (RQ2). Regarding the decision to rate, Models 1 and 2 show that the anticipation in making a reservation is a significant variable: the higher the anticipation, the more chances that a rating will be given. This result implies that a higher anticipation corresponds to a higher expectation, which may lead to more planned purchases, a non-impulse purchase, and a relevant activity at the destination. Therefore, users have a higher tendency to leave a rating after the activity takes place.

The above result is in line with the contentions of expectancy–value theory, which postulates that the motivation to engage in a behavior is influenced by both the individuals' anticipations and the significance that they attribute to the outcome. In this context, the anticipation of a positive trip experience and the value placed on the trip act as driving forces that motivate users to write an online review. Consistent with the results of Köchling and Lohmann (2022), we find that the emotional investment in users' anticipation and preparation for their trip can increase their inclination to share their trip experiences and emotions through online reviews. Moreover, in accordance with Skavronskaya et al. (2020), we find that the act of anticipating a trip can enhance users' retention of details about their trip, thus enabling them to provide a thorough and comprehensive review, especially if they have high levels of anticipation prior their trip.

This finding also ratifies cognitive dissonance theory's self-justification and social validation. As mentioned earlier, individuals engage in self-justification to uphold the consistency in their beliefs and actions (Goethals, 1992), and composing a favorable online review can function as a means of self-justification. This process confirms to themselves and others that their high level of anticipation is well-founded and that they have made a wise decision by booking their trip. With regard to social validation, given that people often seek validation for their choices and experiences from their social circles (Hillman et al., 2023), by sharing a positive review, they can also receive external validation from their social networks. The positive reactions of others to their review can bolster their conviction that they have made the correct choice in booking their trip.

However, anticipation does not have any impact on rating. According to cognitive dissonance theory, a high anticipation may prompt positive or negative online reviews, thereby balancing out the final rating. If a user has a negative experience with a product or service but initially held a positive attitude or expectation, then s/he may experience cognitive dissonance. To reduce this discomfort, s/he may write a review as a way to align his/her beliefs (negative experience) with his/her previous positive attitudes or expectations. In this case, a negative review can be seen as a user's attempt to reduce the dissonance by expressing his/her dissatisfaction with a product or service. However, while cognitive dissonance can be a useful framework for understanding the motivation behind negative online reviews resulting from dissatisfaction, users may be not necessarily driven by cognitive dissonance when writing a negative review. Other factors, such as genuine dissatisfaction or a desire to inform others, can also contribute to negative reviews, especially in the case where users have high anticipation and need to vent out their feelings.

The price paid for the activity also emerges as a significant variable. Those activities with higher prices tend to receive more and higher ratings. This result is in line with the contentions of expectancy–value theory, which posits that making a substantial financial commitment to a trip usually leads to increased expectations, and this positive anticipation should incentivize users to write a review. Meanwhile, a trip that incurs a significant cost is perceived as a valuable experience, and users may regard the price they paid as a substantial investment and thus ascribe a greater value to their trip. In this case, leaving a review becomes a means for them to express and confirm the value that they link to their experience. Following this theory, those users with high expectations and valuations of their expensive trips are more motivated to post a review as they believe that this review will allow them to convey the value that they have gained and the alignment between their expectations and actual experience.

The result that higher prices lead to better evaluations can be explained by the fact that higher-priced activities are inherently better. Nevertheless, the framework of cognitive dissonance theory provides an interesting angle to this result. If the actual experience of a costly trip meets or surpasses their positive expectations, then users should enter a state of cognitive consonance. In this scenario, a convergence can be observed between the users' pre-trip beliefs (expecting a premium experience due to the high cost) and post-trip reality (experiencing a premium trip). Thus, writing a positive online review would be justified. However, if disparities emerge between their expectations and actual trip experience, then users may experience cognitive dissonance. In this case, composing an online review can function as a means for these users to alleviate their cognitive dissonance. Specifically, they may choose to write positive reviews to rationalize their financial investments and alleviate any dissonance they may be feeling. Although they feel dissatisfied, in order to reduce their cognitive dissonance, some users may still write a positive review to justify their investment. Recall that the principles of self-justification and social validation are also applicable to price (Goethals, 1992; Hillman et al., 2023) and may play a central role in cases of cognitive dissonance. The act of posting an online review can serve as a form of self-justification, confirming to users and others that their financial commitment is justified and that they have made a sound decision in booking their expensive trips. In the same vein, sharing a review also elicits social validation from peers and the broader online community.

We also find that a bigger booking group corresponds to a poorer final review. Our database includes bookings that were made for 1 person and for groups of as many as 15 people. Those bookings for larger groups tend to have lower customer satisfaction, indicating that users prefer small groups, which may allow for a more personalized experience.

Those activities that take place on weekends have a lower chance of being rated probably due to the fact that those who go on weekend excursions are workers who do not have any time to write a review after their trip due to their work responsibilities. Meanwhile, those users who participate in activities during weekdays are probably on holiday, thus giving them some time to post a review.

Countries of origin do not have any impact on users' decision to rate (RQ4). Users from Belgium and Spain have a higher tendency to leave ratings. Alternatively, the rating is coherent with the trend of the globalization of online comments and behaviors. Therefore, the differences among cultures (Hofstede, 2011), such as the individualism versus collectivism continuum, are increasingly being blurred by the globalization enabled by the Internet.

However, even if the country of origin does not affect users' decision to rate or their rating, some differences may be observed in the text review that accompanies the numerical rating. In this sense, we provide an initial exploratory analysis of the more frequent topics mentioned by users who review in Spanish, English, and German which is the objective of our RQ5. These sets of comments show some differences.

The other variables are not relevant (i.e., the time of day in which the activity takes place, the days passed until the review is placed, and the type of activity). With regard to days passed until a review is placed, different memory biases may kick in and affect users differently depending on the amount of time that passed. However, our results contradict this notion, that is, this variable does not have any effect on ratings. In response to RQ3, we find that type of activity does not influence users' decision to rate or their rating.

6.1 Implications for theory

The results for the relationship between high anticipation of booking a trip and the behavior related with posting an online review have several theoretical implications.

First, these results support the core tenets of expectancy–value theory, which posits that the motivation for a specific behavior is determined by both the individual's expectations of achieving a particular outcome and the perceived value or desirability of that outcome. In the case of our study, users anticipate a positive outcome from their trip (an enjoyable and exciting experience), and they place high value on sharing this experience through an online review. These results confirm that the theory's framework of motivation holds true in the context of online reviews for trips. These findings also highlight the role of anticipation as a crucial motivational factor given that users' high anticipation for a trip serves as a significant driver for posting online reviews. The emphasis of this theory on expectancy as a motivator is reinforced, thus showcasing how positive expectations can lead to specific behaviors. These results also underscore the concept of subjective value attribution also postulated by expectancy–value theory. Individuals subjectively attribute a high value to the act of sharing their trip experiences through a review. The idea that value is not an objective measure but is influenced by an individual's perception and subjective assessment as posited by this theory is exemplified here. These results also highlight the influence of emotional investment on decision making and behavior. Anticipation often involves emotional investment, and the stress of this theory on value suggests that this investment can significantly impact users' motivation to act, hence underscoring the emotional and affective dimensions of expectancy and value.

Second, these results highlight the role of cognitive dissonance theory in understanding how users seek to maintain alignment between their pre-trip expectations (e.g., anticipating a premium experience due to the high cost) and their post-trip experience (e.g., experiencing a premium trip). When their experience aligns with their positive expectations, users experience cognitive consonance. However, when they observe disparities between their expectation and reality, these users experience cognitive dissonance. These findings suggest that posting an online review can serve as a mechanism for reducing cognitive dissonance. When users experience cognitive dissonance due to their unsatisfied expectations, they may be motivated to write a review as a way of reconciliating the conflict and justifying their financial investment. The use of cognitive dissonance theory in studying post-experience behavior emphasizes its practical applicability in understanding how people seek cognitive consonance after making significant decisions. Additionally, these results highlight the complexity of decision-making processes and the psychological mechanisms that individuals employ to maintain cognitive consistency. This complexity extends to post-purchase behaviors, such as the decision to post online reviews, thereby emphasizing the ongoing nature of cognitive processes beyond the initial decision. The temporal aspects of cognitive dissonance theory also come into play. Results show that the timing of dissonance reduction (post-trip, through a review) is essential. Understanding the temporal dimensions of dissonance resolution is crucial to thoroughly understand how individuals manage cognitive conflicts.

Previous studies have explored the topic of online reviews in different sectors (e.g., Ye et al., 2009 in tourism; Chevalier & Mayzlin, 2006 for the case of books; Liu, 2006 for movies). One of the main problems faced by these studies is the validity and representativeness of their data, that is, whether the ratings posted on social media are significantly biased. Our results show that certain variables can affect users' decision to rate and their ratings. On the one hand, price has an impact on their decision to rate and their final rating. On the other hand, advanced purchase tends to indicate a more planned purchase and induces more willingness to rate. However, the specific characteristics of the service (type of activity and morning vs. afternoon activities) or customers (number of participants, the presence of children in the group, and the country of origin of participants) do not affect the online behavior being analyzed. Therefore, the type of activity, the nationality of participants, and the number of participants do not affect users' decision to post a review and their rating. Interestingly, two characteristics of the booking, namely, price and anticipation, explain these users' decision to rate and rating scores. This finding suggests a relationship between online review behavior and some booking variables. An overall interpretation of these two variables may lead to the argument that the value of a trip results in different online review behaviors.

In our dataset, approximately 1/4 of all bookings received a rating. As mentioned above, the price of the booking and the advanced purchase may explain users' decision to rate. To the best of our knowledge, this type of result has not been reported in the literature given that the databases used in these studies often do not contain full information on all the bookings made and all the reviews written. This finding suggests that despite the high volume of published online reviews, the unexplored opinions represent a high proportion that might mask different online reviews. If the higher price of bookings and long anticipation time are associated with more planned trips compared with last-minute or cheaper trips, then the published online reviews may reflect that users' review behavior depends on the value of their trip.

6.2 Implications for practice

Receiving high online ratings should be among the objectives of anyone that sells goods or provides services given that these ratings can have a direct impact on their sales (Ye et al., 2009). However, having more ratings, regardless of level, has been found to positively affect the overall rating (Melián-González et al., 2013). We do not imply that some customers should be treated differently depending on the chance that they will rate an activity. We find that this process has two key variables, that is, those users who have booked an activity with higher anticipation or an activity with high prices have higher chances of leaving a rating. Therefore, practitioners should encourage those customers who have made their bookings near the activity date to leave a rating, thus reducing the possible bias and gaining more ratings for an activity.

7 Conclusions, limitations, and further research

By using a database containing information on 3,047 activity bookings and 759 ratings associated with these bookings, we generate several meaningful conclusions. First, approximately 1/4 of all bookings in our database were given a rating. Two variables affect users' decision to rate, namely, anticipation (i.e., more days passed from the booking to the activity correspond to a higher chance of leaving a rating) and price (i.e., a higher price corresponds to a higher chance of leaving a rating). The users' country of origin does not have any impact on their decision to rate (in our models, only two countries of origin show a significant difference, which may likely be due to the size of our database). However, our exploratory analysis of the text reviews highlights differences in the main concepts that were emphasized by those users who wrote their reviews in Spanish, English, and German. While we could not investigate these issues in depth due to the size of our database, they open up avenues for future research.

Our database collected from a travel agency is considered unique as it presents a full trace of users' activities, starting from their booking to their rating. However, our study is not free from limitations, which may point toward possible directions for future research. First, our database is limited in scope. We only considered bookings of activities in a single geographical region (Canary Islands) that were made on a single online platform (GetYourGuide). These two constraints can limit the generalizability of our findings. Future research might address social influences, personal preferences, and external circumstances that complement our findings. Second, while the number of bookings and ratings (3,047 and 759, respectively) we included in our analysis is large enough to serve the main purposes of our work, this sample size does not allow a detailed analysis of the differences in behaviors among countries of origin. Third, our data exclude other information, such as the age or tech-savviness of users and whether the booking and rating were made at the users' country of origin or at the tourist destination. Fourth, our database only covers those users who made their bookings and ratings on the same platform. On the one hand, this case provides a certain level of homogeneity in our analysis of different activities because all ratings are related to a trip. On the other hand, many cases of online ratings do not take place on the same platform on which the booking took place, similar to the case of the most popular online rating platform, TripAdvisor. Fifth, our analysis relies on online ratings as the primary data source. Future research could enhance this approach by incorporating neurophysiological tools to examine emotional responses to pictorial content, consistent with the methodology proposed by Bigne, Chatzipanagiotou, and Ruiz (2020). Sixth, one final limitation of our study pertains to the exploratory analysis of user comments. Out of the 759 ratings in our dataset, we processed only 76 comments in Spanish, 86 comments in English, and 120 in German, which account for 72%. While these comments provide valuable qualitative insights into the types of content users post during their trips, the small sample size by language may not fully represent the broader user base. Consequently, the findings from this exploratory analysis should be interpreted with caution and are intended to complement rather than drive the main conclusions of the study. Future research with a larger and more representative sample of user comments could provide more comprehensive insights into user behavior and content characteristics.

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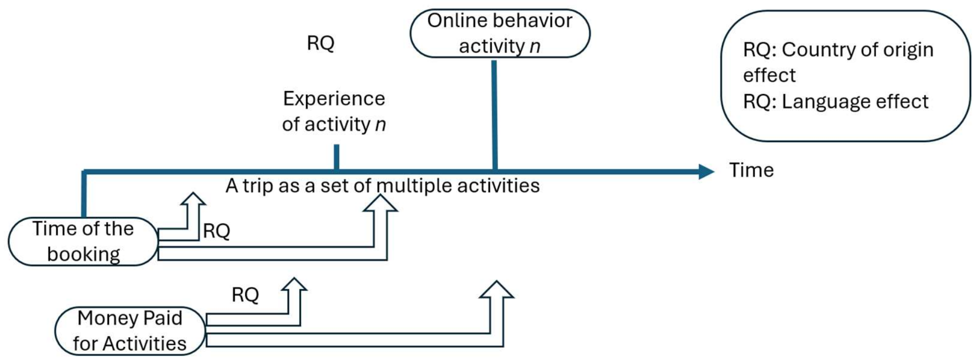
Figure 1. A trip as a set of multiple activities and research objectives



Source: Own elaboration

Figure 2. Marginal effect of anticipation

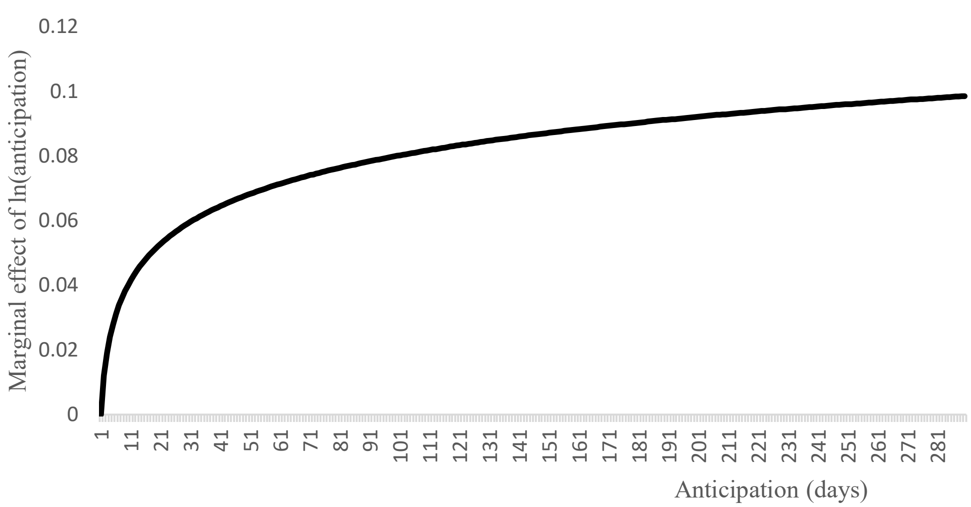
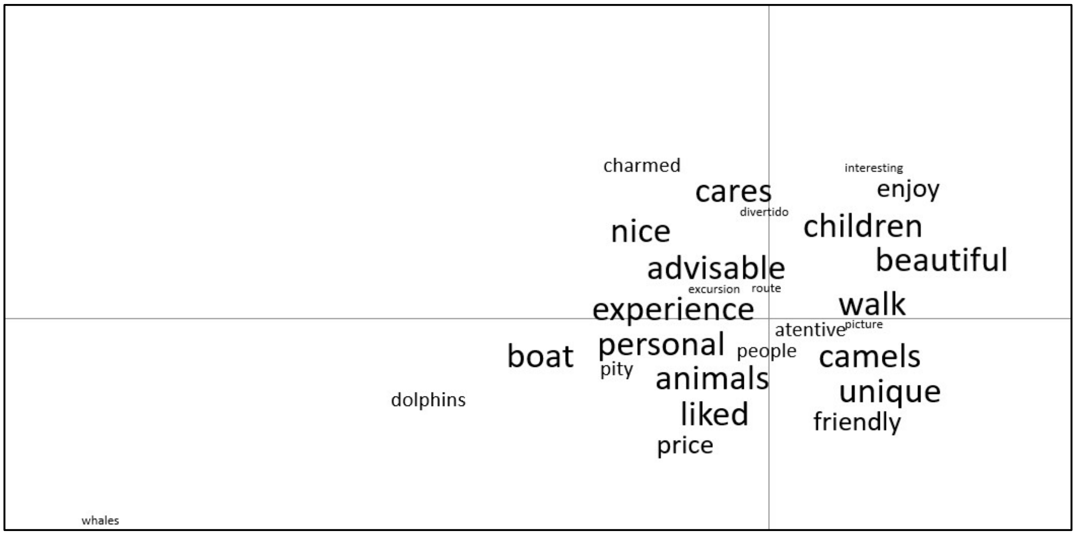


Figure 3a. WordMap analysis for reviews in Spanish (words)



NOTE: Words in the figure have been translated to English after the analysis

Figure 3b. DocuMap analysis for reviews in Spanish (ratings)

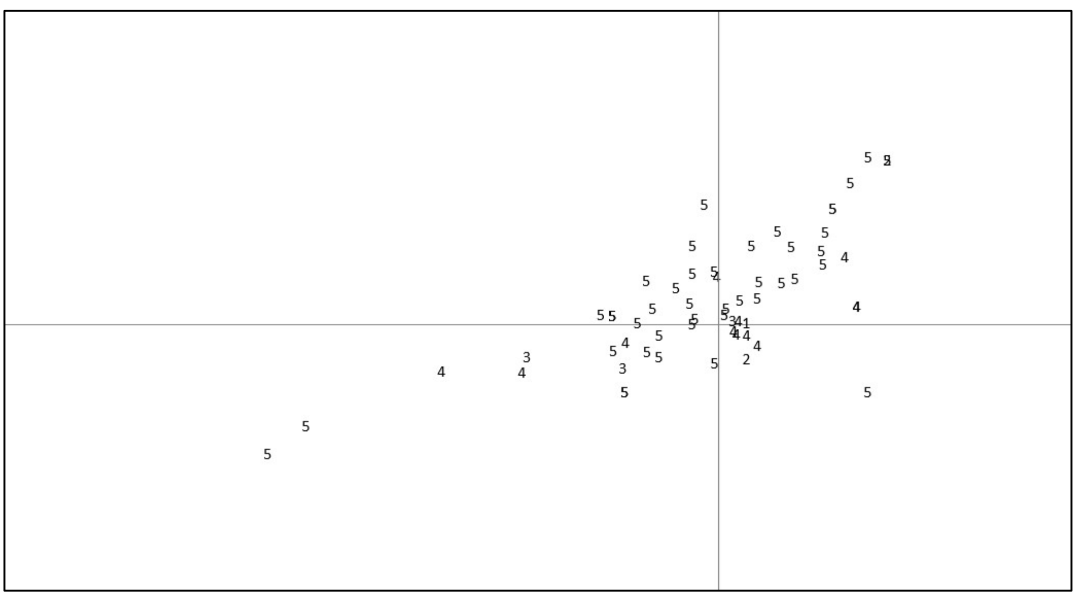


Figure 4a. WordMap analysis for reviews in English (words)

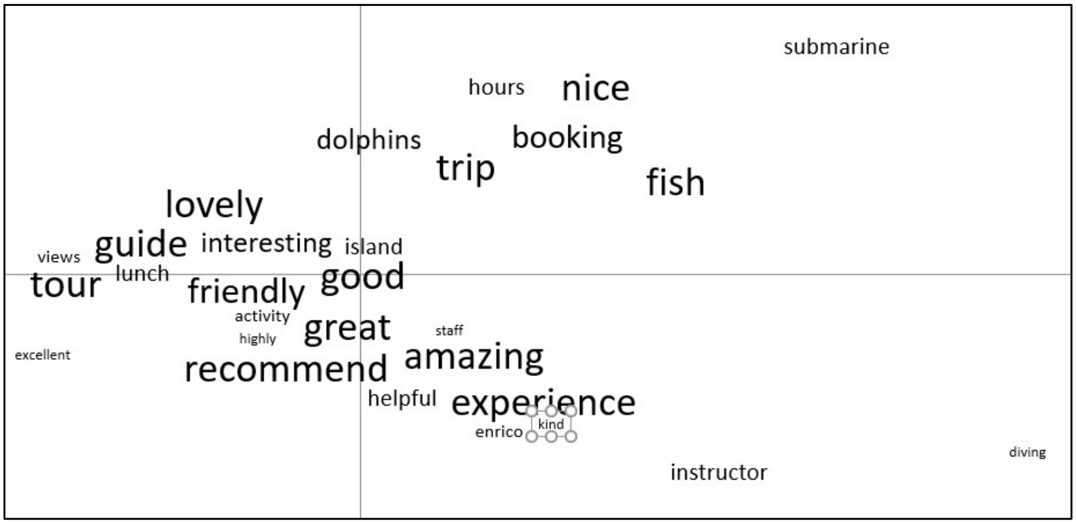


Figure 4b. DocuMap analysis for reviews in English (ratings)

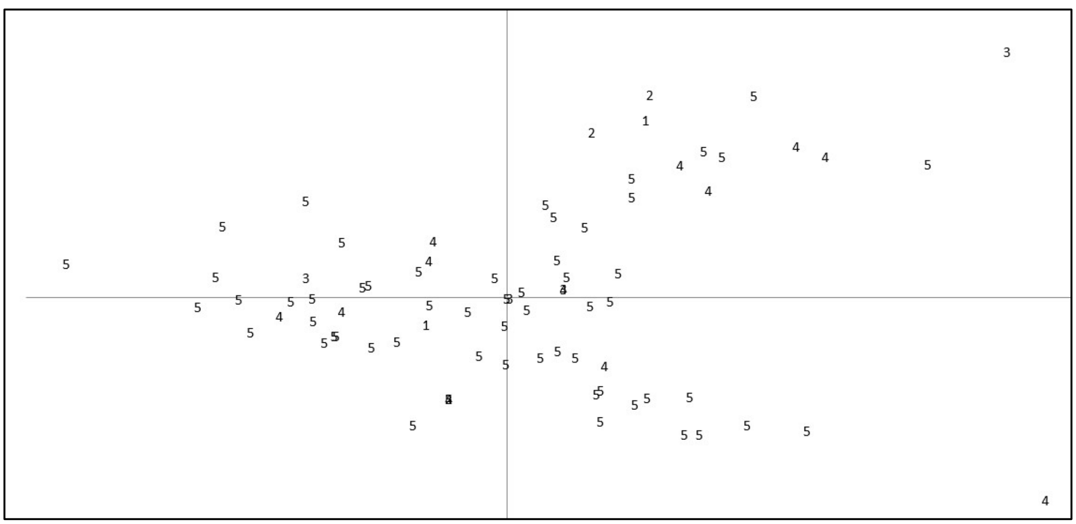


Figure 5a. WordMap analysis for reviews in German (words)

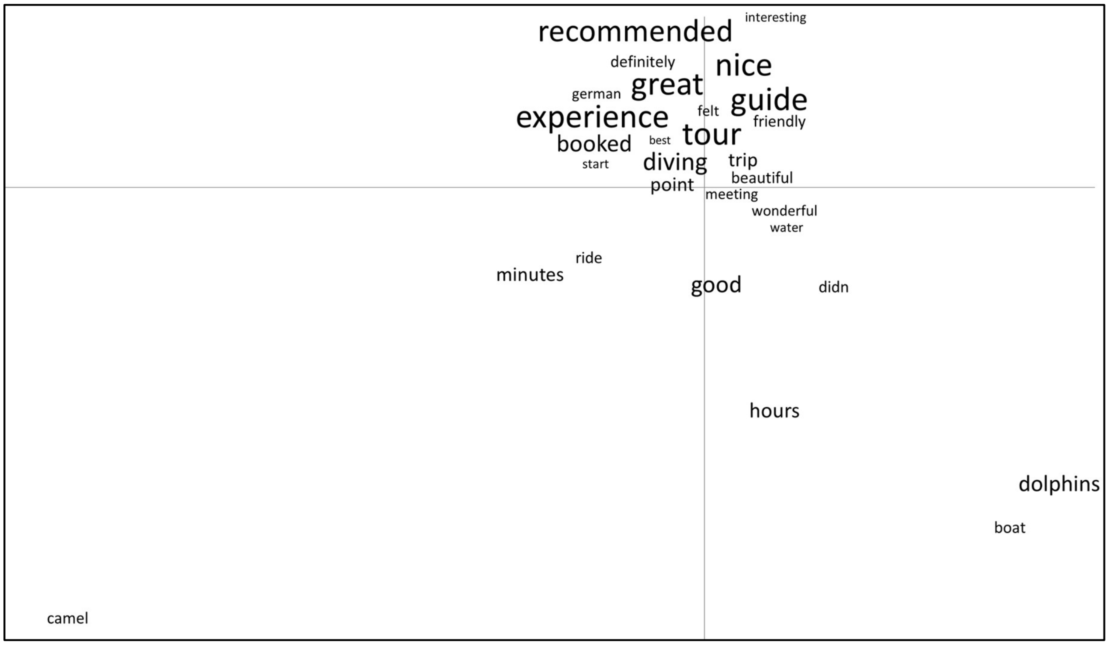


Figure 5b. DocuMap analysis for reviews in German (ratings)

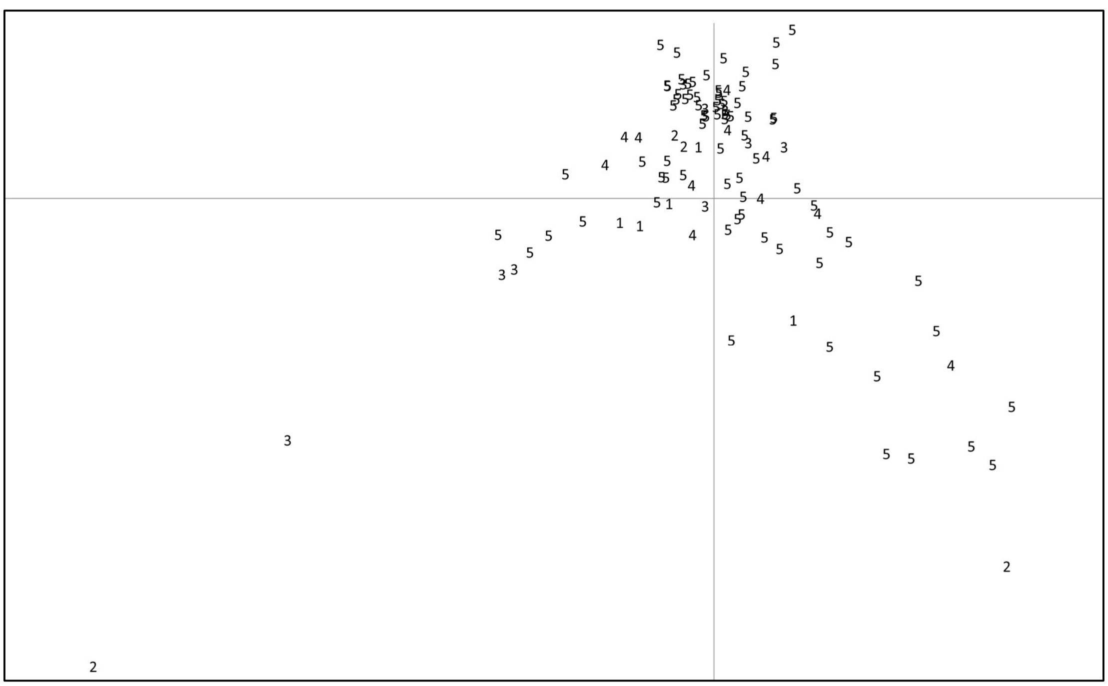


Table 1. Determinants of ratings

	Model 1		Model 2	
	Decision to post a review	**Rating**	**Decision to post a review**	**Rating**
Booking variables				
Price	0.001 (0.001)**	0.001 (0.001)*		
Price per person			0.003 (0.001)***	0.003 (0.001)**
Number of adults	−0.037 (0.026)	−0.046 (0.037)		
Number children	−0.071 (0.051)	0.038 (0.075)		
Moment of the activity				
Morning	0.032 (0.077)	0.037 (0.106)	0.031 (0.077)	0.031 (0.106)
Afternoon	0.093 (0.076)	0.024 (0.107)	0.091 (0.076)	0.013 (0.107)
Weekend	−0.16 (0.059)***	−0.104 (0.103)	−0.157 (0.059)***	−0.108 (0.102)
Time variables				
Days anticipation (log)	0.04 (0.018)**	0.003 (0.029)	0.039 (0.018)**	0.002 (0.029)
Days until review		−0.006 (0.006)		−0.007 (0.006)
Type of activity				
Tickets	−0.021 (0.169)	−0.217 (0.233)	−0.01 (0.169)	−0.236 (0.232)
Excursions	0.082 (0.154)	−0.207 (0.214)	0.092 (0.153)	−0.229 (0.213)
Other activities	−0.016 (0.150)	−0.207 (0.208)	−0.005 (0.150)	−0.229 (0.207)
Country of origin of the tourists				
Germany	0.126 (0.112)		0.131 (0.112)	
Spain	0.262 (0.114)**		0.267 (0.114)**	
United Kingdom	0.057 (0.128)		0.061 (0.128)	
The Netherlands	0.072 (0.143)		0.085 (0.143)	
Italy	0.055 (0.148)		0.07 (0.148)	
France	0.232 (0.168)		0.241 (0.168)	
Switzerland	0.229 (0.179)		0.242 (0.179)	
Sweden	0.195 (0.190)		0.201 (0.190)	
Belgium	0.391 (0.207)*		0.408 (0.207)**	
Norway	0.235 (0.203)		0.245 (0.203)	
Ireland	0.181 (0.223)		0.19 (0.223)	
Austria	−0.043 (0.219)		−0.03 (0.219)	
Denmark	−0.078 (0.228)		−0.052 (0.226)	
Constant	−0.905 (0.200)***	5.094 (0.665)***	−1.033 (0.194)***	5.018 (0.685)***
AIC	2.082		2.078	
SIC	2.153		2.141	
ρ	−0.971 (9.2E−05)***		−0.971 (9.2E−05)***	

NOTE: ***p < 0.01, **p < 0.05, *p < 0.1.

Table 2. Determinants of ratings with alternative specifications (linear anticipation)

	Model 3		Model 4	
	Decision to post a review	**Rating**	**Decision to post a review**	**Rating**
Booking variables				
Price		0.001(0.001)*		
Price per person	0.001(0.0004)*		0.003(0.001)***	0.003(0.001)*
Number of adults	-0.037(0.026)	-0.047(0.037)		
Number children	-0.077(0.051)	0.036(0.075)		
Moment of the activity				
Morning	0.035(0.077)	0.039(0.107)	0.034(0.077)	0.033(0.106)
Afternoon	0.103(0.076)	0.026(0.109)	0.101(0.076)	0.017(0.108)
Weekend	-0.167(0.059)**	-0.107(0.105)	-0.164(0.059)**	-0.113(0.103)
Time variables				
Days anticipation	0.003(0.001)	-0.002(0.001)	0(0.001)	-0.002(0.001)
Days until review		-0.006(0.006)		-0.006(0.006)
Type of activity				
Tickets	-0.014(0.169)	-0.213(0.235)	-0.002(0.169)	-0.232(0.233)
Excursions	0.091(0.153)	-0.21(0.215)	0.102(0.153)	-0.231(0.214)
Other activities	-0.005(0.15)	-0.202(0.21)	0.008(0.15)	-0.224(0.208)
Country of origin of the tourists				
Germany	0.134(0.112)		0.139(0.112)	
Spain	0.27(0.114)*		0.275(0.114)*	
United Kingdom	0.054(0.128)		0.058(0.128)	
The Netherlands	0.069(0.143)		0.082(0.143)	
Italy	0.054(0.148)		0.069(0.148)	
France	0.229(0.168)		0.239(0.168)	
Switzerland	0.223(0.179)		0.236(0.179)	
Sweden	0.186(0.19)		0.193(0.19)	
Belgium	0.412(0.207)*		0.429(0.207)*	
Norway	0.219(0.203)		0.23(0.203)	
Ireland	0.159(0.222)		0.169(0.222)	
Austria	-0.035(0.218)		-0.021(0.218)	
Denmark	-0.078(0.228)		-0.05(0.226)	
Constant	-0.869(0.199)***		-1.002(0.194)***	
AIC	2.088		2.083	
SIC	2.159		2.146	
ρ	−0.971 (9.21E−05)***		−0.971 (9.22E−05)***	

NOTE: ***p < 0.01, **p < 0.05, *p < 0.1.

Table 3. Determinants of ratings with alternative specifications (quadratic anticipation)

	Model 1		Model 2	
	Decision to post a review	**Rating**	**Decision to post a review**	**Rating**
Booking variables				
Price	0.001(0.0004)*	0.001(0.001)*		
Price per person			0.003(0.001)**	0.003(0.001)*
Number of adults	-0.037(0.026)	-0.048(0.037)		
Number children	-0.076(0.051)	0.034(0.075)		
Moment of the activity				
Morning	0.032(0.077)	0.038(0.106)	0.031(0.077)	0.032(0.105)
Afternoon	0.098(0.076)	0.028(0.107)	0.096(0.076)	0.018(0.107)
Weekend	-0.166(0.059)**	-0.112(0.104)	-0.163(0.059)**	-0.117(0.103)
Time variables				
Days anticipation	0.003(0.002)	0.001(0.003)	0.003(0.002)	0.001(0.003)
Days anticipation2	-0.00001(0.00001	-0.00001(0.00001)	-0.00001(0.00001	-0.00001(0.00001)
Days until review	0.132(0.112)	-0.006(0.006)	0.137(0.112)	-0.007(0.006)
Type of activity				
Tickets	-0.012(0.169)	-0.205(0.233)	-0.0001(0.169)	-0.224(0.231)
Excursions	0.091(0.153)	-0.207(0.214)	0.102(0.153)	-0.229(0.213)
Other activities	-0.007(0.15)	-0.201(0.208)	0.005(0.15)	-0.223(0.206)
Country of origin of the tourists				
Germany	0.132(0.112)		0.27(0.114)*	
Spain	0.265(0.114)*		0.056(0.128)	
United Kingdom	0.052(0.128)		0.086(0.143)	
The Netherlands	0.073(0.143)		0.069(0.148)	
Italy	0.054(0.148)		0.24(0.168)	
France	0.23(0.168)		0.238(0.179)	
Switzerland	0.225(0.179)		0.193(0.19)	
Sweden	0.186(0.19)		0.419(0.207)*	
Belgium	0.402(0.207)*		0.232(0.203)	
Norway	0.222(0.203)		0.187(0.222)	
Ireland	0.177(0.222)		-0.023(0.218)	
Austria	-0.036(0.218)		-0.05(0.225)	
Denmark	-0.077(0.228)		0.27(0.114)*	
Constant	-0.879(0.200)***			-1.01(0.194)***
AIC	2.084		2.079	
SIC	2.159		2.147	
ρ	−0.971 (9.22E−05)***		−0.971 (9.24E−05)***	

NOTE: ***p < 0.01, **p < 0.05, *p < 0.1.