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Effects of negative sentiment and review length on ratings, as moderated by social turbulence and hotel quality

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Abstract

Purpose—By advancing understanding of the effects of electronic word of mouth (eWOM) in the hospitality industry, the current study offers insights that can help hotel practitioners make better informed decisions, improve tourists' experiences, enhance their reputations, and gain economic benefits.

Design/methodology/approach—With a sample of negative online reviews, this study specifies the direct impacts of negative sentiment and review length on hotel ratings and the moderating influences of review length, social turbulence due to COVID-19, and hotel quality. The sample covers a two-year period (2019 and 2021) and comprises 19,441 online textual reviews written by Spanish tourists, referring to 121 4-star hotels in the Canary Islands. The analyses rely on NVivo 15 and SPSS 28.

Findings—The results confirm that both negative sentiment and review length negatively affect hotel ratings. Review length and social turbulence increase the effect of negative sentiment on ratings; hotel quality mitigates the negative effect of review length.

Originality/value—This study addresses an important research gap and calls for more in-depth studies of the hospitality industry to clarify the relationship of eWOM content with ratings. It establishes a comprehensive, novel, and contemporary framework that integrates several theories and applies them in a relevant, popular global tourism destination.

Research limitations—The study results are limited to reviews posted only on Booking.com.

Keywords—Negative sentiment, Review length, Ratings, COVID-19 pandemic, Hotel quality

Paper type—Research paper

1. Introduction

Electronic word of mouth (eWOM) provides various signals that potential customers can use and interpret to inform their purchase decisions (Browning *et al*., 2013; Xie *et al*., 2016; Xie *et al*., 2017). For example, the average review rating, a quantitative measure linked to eWOM, offers a proxy of the firm's reputation that influences sales (Browning *et al*., 2013; Nieto *et al*., 2014). Potential customers generally perceive eWOM as more trustworthy than company communications, because it is produced by their peers and does not have an explicitly commercial purpose (Bickart and Schindler, 2001; Park *et al*., 2007; Sparks *et al.*, 2013). Acknowledging its relevance, companies thus have started to include eWOM on their own websites, though such customer feedback also appears on other online sites, making it difficult to monitor and control.

Still, it is critical to manage eWOM effectively, especially in the hospitality industry, where it can determine firms' competitiveness and success (Bughin *et al*., 2010; Hernández-Maestro, 2020; Litvin *et al*., 2008; Mate *et al*., 2019; Ye *et al*., 2011). Hotel consumers frequently seek out eWOM for guidance and to reduce their uncertainty (Hernández-Maestro, 2020; Mauri and Minazzi, 2013; Papathanassis and Knolle, 2011; Ye *et al*., 2009, 2011), and such information is readily available on online platforms that feature tourism consumers' feedback (e.g., TripAdvisor). According to 2021 estimates by TripAdvisor, three-quarters of travelers cite online reviews as extremely or very important to their travel decisions. Thus, eWOM and its related variables appear strongly associated with business performance in the hospitality industry (Phillips *et al*., 2017; Viglia *et al*., 2016; Ye *et al*., 2009).

Extant literature acknowledges that online ratings influence consumer decision-making (Casaló *et al*., 2015b; Rani and Shivaprasad, 2021) and also has established that negative feedback is more influential than positive feedback (Casaló *et al*., 2015a). Studies that consider the relationships between review characteristics and ratings indicate that both negative sentiment in a review (Verhagen *et al.*, 2013) and review length can be linked to negative ratings (Zhao *et al.*, 2019). However, the precise nature of these effects remains uncertain, as the summary of prior literature in Table I reveals. In particular, various contingencies, such as social turbulence and hotel reputation, could moderate the relationships of negative sentiment, review length, and ratings (Muritala *et al.*, 2022; Nieto *et al.*, 2014). Additionally, when approaching sentiment analysis, research often relies on classifying sentiment as just negative, positive, or neutral (Geetha *et al.*, 2017; Ghasemaghaei *et al.* 2018; Wang *et al.,* 2023). Even research using AI-based sentiment analysis would do so (e.g., Krugmann and Hartmann, 2024). However, our study includes a more in-depth analysis of the sentiment in reviews (fine-grained sentiment analysis) by classifying it as very negative, moderate negative, or neutral instead.

With this study, we seek to offer a timely assessment and establish an integrative, novel research framework. Specifically, we leverage signaling theory and the theory of social sharing of emotions to predict the precise negative effects of sentiment intensity and review length on ratings, as well as a potential moderating role of review length. Furthermore, by integrating terror management theory, we predict enhancement effects linked to negative sentiments and length; by adopting cognitive dissonance theory, we also propose diminishing effects of sentiment and length on ratings. Overall, by combining multiple, well-established theories to study a contemporary research topic, our integrative framework provides a more comprehensive view of the influence of eWOM on hotel ratings.

To develop this framework, we focus on Spain, a top destination for international tourists. In 2023, it welcomed 85.17 million international tourists (arrivals), ranking second behind France (UN Tourism, 2024). The tourism industry thus accounted for 12.3% of Spain's gross domestic product in 2023 (INE, 2025). These indicators of the relevance of the tourism industry identify Spain as a pertinent setting for studying the influences of tourism eWOM.

In the next section, we review literature on eWOM, as well as evidence regarding the influence of review sentiment and review length on ratings. We also detail the social turbulence created by the COVID-19 pandemic and the relevance of hotels' reputation, as potential moderators. In the formal hypotheses, we predict the effects of all these variables on online ratings. After detailing the methodology and results, we conclude with a discussion that offers implications, some limitations, and further research directions.

2. Conceptual framework

2.1. Electronic word of mouth (eWOM)

The term *eWOM* refers to "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Hennig-Thurau *et al.*, 2004, p. 39). For the current study, we focus on reviews posted by hotel guests on the accommodation booking website Booking.com.

We acknowledge the emergence of some new forms of word of mouth, formulated by generative AI (e.g., ChatGPT recommendations), that could influence consumer decision-making (Kim *et al.*, 2023a, 2023b; Tassiello *et al.*, 2024). Despite the substantial potential impacts of such communications, produced through a collaboration between AI technology and consumers, these emergent word-of-mouth inputs remain vulnerable to mistakes and errors. Furthermore, many consumers continue to reject or exhibit aversion toward AI algorithms (Burton *et al.*, 2020), due in part to their privacy concerns (Kim *et al.*, 2023a, 2023b). These limitations, as well as the ease with which consumers can share their thoughts and feelings online, may explain why the influence of eWOM on decision-making seems to be rising, especially in the hospitality industry (Mate *et al*., 2019). Specialized operators like TripAdvisor regularly gauge the value of eWOM; in a 2023 report for example, TripAdvisor identified strong increases (+20%) in review submissions (in 2022, 30.2 million reviews were submitted to the site). As we noted previously, three-quarters of travelers consider online reviews extremely or very important when making travel decisions, and 76% of those surveyed prefer reviews that include paragraph-length descriptions of accommodations (TripAdvisor, 2021). Moreover, 81% of respondents always or frequently read online reviews before booking accommodations (TripAdvisor, 2019). Similarly, a FEVITUR (2023) study determined that 60.3% of stays in Spanish tourist houses (e.g., apartments, villas, bungalows) produced at least one new online review in 2022, higher than the 50.2% reported in 2019.

Accordingly, research into eWOM has established that it provides signals that in turn influence consumers' perceptions and behaviors (Browning *et al*., 2013; Filieri and McLeay, 2013; Mauri and Minazzi, 2013; Moliner-Velázquez *et al*., 2022; Vermeulen and Seegers, 2009). As we noted previously, eWOM appears to have a particularly strong influence on business performance in the hospitality industry (Anagnostopoulou *et al*., 2020; Melo *et al*., 2017; Nieto *et al*., 2014; Phillips *et al*., 2017; Viglia *et al*., 2016; Zhang *et al*., 2019).

Such influences are predicted by both signaling theory (Akerlof, 1970) and attribution theory (Heider, 1958; Kelley, 1973). Consumers use the signals provided by eWOM to reduce the risks implicit to purchases. For example, greater review volume means wider market awareness, such that more others have bought the products, which reduces purchase risk. Ratings also provide cues to help people form expectations. These overall judgments reflect reviewers' judgments of the quality of the offering (Hu *et al*., 2008). Ratings often are available in a Likert-style format, reflecting positive, neutral, or negative quality evaluations (Mudambi and Schuff, 2010). The general consensus in extant literature indicates that product review ratings provide useful information for consumers' purchase decisions (Casaló *et al.*, 2015b; Hernández-Maestro, 2020; Hu *et al.*, 2008; Korfiatis *et al.*, 2012; Lee *et al.*, 2013; Rani and Shivaprasad, 2018, 2021; Salehan and Kim, 2016).

Attribution theory also predicts that people draw conclusions from others' actions. When readers encounter a review, their perceptions and behavior depend on their subjective interpretation of its information. If a review reports a problem, readers must infer if the firm is responsible for the problem (Browning *et al.*, 2013; Filieri and McLeay, 2013; Hernández-Maestro, 2020; Libai *et al.*, 2010; Sen and Lerman, 2007). In such processes, negative feedback is more influential than positive feedback (Casaló *et al.*, 2015a; Chakravarty *et al.*, 2010; Park and Lee, 2009; Sen and Lerman, 2007; Sparks and Browning, 2011), in line with social cognition theory, which suggests that people perceive negative information as more diagnostic. Moreover, negative information is automatically alerting, and stress evokes vigilance to threatening stimuli (Fiske, 1993). In this regard, Pan and Chiou (2011) indicate that negative information about hotels posted on web-based opinion platforms is more trustworthy than positive information. Therefore, high levels of negative reviews can damage brand value, produce unfavorable consumer attitudes (Bambauer-Sachse and Mangold, 2011; Lee *et al.*, 2008), and negatively affect purchase decisions (Fagerstrom and Ghinea, 2011).

Although substantial literature has considered the importance of eWOM for consumers' decision-making, more knowledge still is needed about the nature of the relationship between review characteristics and review ratings (Ghasemaghaei *et al.*, 2016, 2018). Because review sentiment and review length represent significant features of online reviews (Salehan and Kim, 2016), we prioritize the relationships of these features with review ratings.

2.1.1. Review sentiment and ratings. People communicate their emotions for several purposes (e.g., obtaining approval, arousing empathy), as detailed by the theory of social sharing of emotions (Rimé *et al.*, 1992). Rimé *et al.* (1992) describe emotions as natural responses to emotionally arousing events. When an event or experience evokes positive emotions, people are less likely to write negative reviews, whereas negative emotions increase the chances they will do so (Zeelenberg and Pieters, 2004). Emotions such as anger or sadness make people more likely to engage in negative word of mouth (Nyer, 1997); as Verhagen *et al*. (2013) find, negative affect also increases the chance that they write negative reviews. Consumers' sentiments and emotions relate to review ratings too; when consumers write reviews, the ratings they provide are consistent with the sentiments of those reviews (Ghasemaghaei *et al*., 2018). Thus, we propose:

H1. The intensity of the negative sentiment in tourists' online textual reviews negatively affects their review ratings.

2.1.2. Review length and ratings. More detailed descriptions, as appear in longer reviews, denote that customers have put more energy into evaluating products (Burtch *et al.*, 2018; Chevalier and Mayzlin, 2006). Although it might seem logical to predict that people who are enthusiastic about their positive experiences would devote more energy to describing their experience, in reality, consumers tend to exhibit more effort to post reviews following negative experiences (Rohde *et al.*, 2022). These consumers seemingly sense a strong need to vent their negative feelings, restore balance, or warn other potential buyers (Bhattacherjee, 2001; Rohde *et al.*, 2022; Zhao *et al.*, 2019). In turn, they work to write comments that are persuasive (Salehan and Kim, 2016) and prompt identification and understanding among others, which likely requires more words. Longer reviews are more helpful, and they catch readers' attention better (Salehan and Kim, 2016). In general, then, customers write more detailed descriptions of negative aspects than they do of positive aspects (Zhao *et al.*, 2019). They use more words to express the frustration, anger, and depression that results from negative product experiences (Berezina *et al.*, 2016; Ghasemaghaei *et al.*, 2018). In contrast, they submit shorter reviews when they are happier with products (Rohde *et al.*, 2022).

For a given sample of negative online reviews, we thus expect that those that describe particularly negative hotel experiences will be longer and detailed, providing descriptions of "dissatisfiers" (i.e., service elements that produce dissatisfaction). To penalize the offending hotels, these consumers also likely provide lower ratings. In turn, we expect that negative review sentiment exerts a greater effect on ratings when the reviews are longer. This moderating role of review length has not been studied sufficiently (Geetha *et al.*, 2017). In exploratory analyses in the insurance sector, Ghasemaghaei *et al.* (2018) find some initial evidence of an interaction among review sentiment, review length, and ratings. We therefore propose and test two related predictions:

H2. Review ratings are negatively affected by the length of negative online reviews.

H3. Review length enhances the effect of negative sentiment intensity on review ratings.

2.2. Moderating role of social turbulence caused by COVID-19

The COVID-19 pandemic caused substantial social turbulence (Muritala *et al.*, 2022). It altered people's sense of security; the enforced isolation, inability to be with loved ones, lockdown periods, and prospect of becoming sick or dying all changed people's lifestyles. Such shifts also meant substantial declines in tourism. For extended periods, people were not allowed to travel. Even after those restrictions loosened, many people continued to avoid traveling or sought options other than hotels, such as individual houses to rent. Furthermore, the pandemic was associated with increased depression and anxiety (Hu *et al.*, 2020; Oh *et al.*, 2021). Thus, in addition to its direct impact on health through the risk of infection, COVID-19 also affected psychological well-being (Jacob *et al.*, 2020, Pierce *et al.*, 2020, Vindegaard and Benros, 2020) and induced changes in consumers' behaviors.

In particular, during the pandemic, people experienced increased anxiety and emotional distress when interacting with other people, as would be required to consume hospitality offerings. Many people were deeply concerned about how others cared for health (e.g., wore masks, used sanitizer). According to terror management theory, the mortality salience stemming from the pandemic created anxiety by reminding people of the inevitability of death, which is at odds with the human instinct to survive (Greenberg *et al.*, 1986; Hu *et al.*, 2020). Such distress likely was increased by service providers' actions, even appropriate ones, such as screening for health statuses and establishing social distancing. Compared with normal conditions, hotels' adaptation and adoption of new restrictions and service standards negatively affected service delivery and the customer experience, because they produced undesirable outcomes for consumers (e.g., long queues, unavailability).

When people feel greater anxiety, they also tend to adopt more pessimistic views of the world, which in turn inform their product perceptions and evaluations. As previous research shows, customers' evaluations reflect the emotions they feel (Hernández-Maestro *et al.*, 2007; Isen, 1987). Thus, negative sentiment leads to more negative ratings (Ghasemaghaei *et al.*, 2018) and lower intentions to recommend (Wang *et al.*, 2023); it also triggers customers' criticisms and prompts them to provide negative evaluations of their experiences (McColl-Kennedy and Sparks, 2003; Zhao *et al.*, 2019). Because negative emotions (e.g., sadness, anger) were higher during the COVID-19 pandemic (Gerrath *et al.*, 2023), we anticipate:

H4. Due to social turbulence caused by the outbreak of the COVID-19 pandemic, tourists' hotel ratings were lower.

H5. Due to social turbulence caused by the outbreak of the COVID-19 pandemic, the effect of

a) negative sentiment on hotel ratings was enhanced.

b) review length on hotel ratings was enhanced.

2.3. Moderating role of hotel quality

According to cognitive dissonance theory (Festinger, 1957), consumers seek consistency and congruency and assimilate their evaluations with their expectations. For example, if customers have high expectations of a hotel experience and a service failure occurs, they resist providing low ratings or admitting that their expectations were incorrect. Thus, ratings tend to be biased toward expectations (Hernández-Maestro *et al*., 2007; Nieto *et al*., 2014; Rodríguez del Bosque *et al*., 2006). In turn, we expect that customers' experiences of high-quality hotels will prompt better perceptions of those experiences, compared with low-quality hotels, even after a service failure. High-quality hotels enjoy a buffer against service failures. Still, service failures prompt customers to recognize a gap between their expectation and their experience, so they might penalize offending hotels when rating them (Geers and Lassiter, 1999). Accordingly, we hypothesize:

H6. Hotel quality diminishes the strength of the negative relationships between

a) negative sentiment intensity and ratings.

b) review length and ratings.

Figure 1 depicts the conceptual model, which contains all the hypotheses included in our novel theoretical framework.

3. Method

3.1. Data collection

The research data consist of 19,441 online textual reviews published on Booking.com (www.booking.com) by Spanish clients of 121 different 4-star hotels located in the Canary Islands. This category of hotels represents the most common option chosen by travelers in Spain (domestic and foreign). Across the range of 1- to 5-star Spanish hotels, 4-star hotels represent 54% of beds, and they attract 57% of all overnight stays. In contrast for example, in 2024, 5-star hotels represented only 8% of overnight stays (INE, 2025). To collect these reviews, we used the Parsehub data mining software, applied to Booking.com, one of the world's leading online travel agencies (OTA).

We consider this OTA an appropriate source, because Booking.com maintains the highest market share among OTAs in the European hotel industry, at 69.3% in 2023 (HOTREC, 2024). It also features a greater share (37%) of total review volume in the hospitality sector, ahead of Google, Tripadvisor, and Expedia (27%, 12%, and 7%, respectively; Revinate, 2024). Accordingly, it constitutes the most visited tourism website worldwide (e.g., in January 2025, it received 560.23 million visits, while tripadvisor.com got 129.47 million visits; Semrush, 2025). Beyond such quantitative signals of its relevance, Booking.com allows customers to provide extensive comments related to their previous bookings (differentiating between positive and negative aspects), as well as to rate the hotels on a scale. Finally, Booking.com eliminates offensive language and verifies reviews' authenticity before publishing them, to ensure the reviews are written by actual consumers.

The data, which we collected in December 2021, consist of comments posted in the years 2019 and 2021, with all duplicate and non-complete cases identified and eliminated. In September 2019, Booking.com changed its ratings scale system, from a 2.5–10 scale to a 1–10 scale. For the purposes of this study, we rescaled the ratings from the old system to match the 1–10 range (Martin-Fuentes *et al.*, 2024; Mellinas and Martin-Fuentes, 2021). After collecting all comments for the analyzed period (112,433), we identified those that explicitly indicated some negative aspects of the hotel experience (19,441). In Tables II and III, we present details about the review and hotel samples, including review ratings, number of nights, type of company, and year (before or during COVID-19), as well as the hotel price, hotel rating, and hotel quality category.

3.2. Analyses and measures

We used NVivo 15 and SPSS 28 to analyze the data. In particular, we applied NVivo 15 to detect the various sentiments and topics. This software employs machine learning to detect themes or sentiment automatically, and it supports the conversion of qualitative data into quantitative information (see Appendix I). Then we ran the database preparation and regression analyses using SPSS 28. Table IV lists the key variables. In three regression analyses, we rely on the overall rating score that the reviewer offers for their experience at the hotel (i.e., *Review rating*) as the dependent variable.

Regression 1 examines the effects of the control variables on review ratings. First, noting its potential relationship with ratings (Melo *et al*., 2017; Shugan, 1984; Zhang *et al.*, 2020), we used the price per person and night (for a standard room) as a control variable (*Price*). We expected a positive sign for this control variable; higher prices generally imply a higher quality offer, so high prices should incite consumers to expect high quality. If the firm fulfills these expectations, their ratings will be high; if it fails, prices ultimately will need to decrease (Melo *et al*., 2017; Shugan, 1984; Zhang *et al*., 2020). Second, we included dissatisfiers as control variables, with the prediction that their mentions in reviews decrease ratings (Melo *et al.*, 2017). To identify dissatisfiers, we used NVivo's automatic main topic detection tool, assigning a value of 1 to identifications of the following topics and 0 otherwise: *Food* (variety, meals, buffet, breakfast, beverages, all-inclusive), *Swimming pool* (size, hammock, opening times), *Room* (cleaning, maintenance, decoration), *Quality* (price–quality relationship, hotel quality), and *Front-desk* (check-in, check-out, personal attention). We also searched for *COVID-19* (pandemic, masks, sanitizers) mentions as another control variable.

Beyond these control variables, Regression 2 adds the direct effects of four independent variables: identification of negative sentiment intensity (*Negative sentiment*), length of review (*Review length*), whether the review was issued before or during the COVID-19 pandemic (*Social turbulence*), and hotel reputation (*Hotel quality*). We used NVivo's sentiment detection capability to construct *Negative sentiment*, such that it assigned values of 1 to neutral sentiment, 2 to moderate negative sentiment (adjectives related to mild negative emotion, like "dirty"), and 3 to intense negative sentiment (adjectives and adverbs related to intense emotions, like "horrible," "disgusting," "very noisy"). *Review length* equaled 1 if the number of characters in the review exceeded the median (99 characters) and 0 otherwise. For *Social turbulence*, we assigned values of 1 for 2021 and 0 for 2019. *Hotel quality* equaled 1 if its score exceeded the median of the average ratings (8.4) and 0 otherwise. The average rating for each hotel in the sample is calculated by Booking.com, for the most recent 36 months (i.e., mean value of individual scores for the hotel's reviews for 2019, 2020, and 2021, as well as for the 112,433 observations).

Finally, Regression 3 added interaction terms to Regression 2. Specifically, we accounted for *Negative sentiment × Review length, Negative sentiment × Social turbulence, Review length × Social turbulence*, *Negative sentiment × Hotel quality,* and *Review length × Hotel quality.*

4. Results

The results of our analysis in Table V confirm that negative sentiment intensity and review length relate negatively to ratings, as we predicted in H1 and H2. Regarding the moderating effects, we find support for H3, in that review length enhances the effect of negative sentiment. The pandemic period, beyond its direct and negative effect on ratings (H4), also enhances the negative effect of negative sentiment (H5a), though not the negative effect of review length (H5b). Besides, we cannot confirm H6a, because hotel quality does not diminish the link between sentiment intensity and ratings (that is, the effect of the interaction of negative sentiment × hotel quality (average rating) is not significant). However, Table V shows that hotel quality (average rating) diminishes the effects of review length on ratings (B = 0.141, p = 0.010), in support of H6b. Figure 2 contains the interaction plots that represent all the moderating effects. When we reran Regression 3 with only those reviews containing negative sentiment and replaced the average rating with a hotel response variable as an alternative proxy for hotel quality (dichotomous variable, = 1 if the hotel responds, 0 otherwise), we confirmed the support for H6b. When negative sentiment exists, a hotel response weakens the effects of review length on ratings (B = 0.798, p = 0.028). Finally, the control variables produced the expected results: Hotels with higher prices obtained higher ratings, and dissatisfiers related negatively to ratings, though the swimming pool variable is not significant after we introduce negative sentiment and review length. Table VI lists the results of each hypothesis test.

As the variance inflation factors (VIF) in Table V show, multicollinearity does not appear to be an issue. All the VIFs are below the stringent threshold of 2.5 (Johnston *et al.*, 2018). We also conducted some additional analyses to confirm the robustness of our empirical results. First, we adopted an alternative methodology and tested the model by applying partial least squares structural equation modeling (PLS-SEM) in SmartPLS (Ringle *et al.*, 2024), across 5,000 subsamples. We also tested separate models for each moderating effect, by both regression analysis and PLS-SEM. The results, summarized in Appendix II, offer consistent support for the findings in our main analysis. Second, as reported, our use of hotel responses as an alternative measure of hotel quality provides further confidence in the robustness of our findings.

5. Discussion and implications

The COVID-19 pandemic period offers an interesting framework for analyzing negative reviews, especially when compared with a pre-pandemic context. The pandemic changed lifestyles and created social turbulence, especially for tourism markets. It was not easy for hotels to adapt to COVID protocols; fulfilling legal requirements often damaged service delivery (e.g., long queues for guests, fewer options, closed gyms). Moreover, the pandemic was a time of distress, tension, and uncertainty that affected people's emotions, attitudes, perceptions, and behaviors.

By using qualitative and quantitative methods, this study furthers understanding of the effects of negative sentiment and review length for Canarian hotels, before and during the COVID-19 pandemic (2019 and 2021). It remains challenging to identify the effects of review length and negative sentiment on ratings, yet our analyses confirm their negative effects and further identify a significant interaction between negative sentiment and review length. Thus, congruity exists between sentiment and rating; written reviews also are longer if the sentiments are negative. Negative sentiments expressed in long reviews intensify the effect of those sentiments on ratings.

The post-pandemic (vs. pre-pandemic) period also was negatively associated with ratings. We acknowledge that, due to the differences between the old and new Booking.com scales, the data might show a decrease in ratings (e.g., Martin-Fuentes *et al.*, 2024; Mellinas and Martin-Fuentes, 2021). Even after rescaling though, the reduction in ratings remains significant, suggesting that the ratings drop actually is produced by changes in consumers' attitudes and behaviors due to the pandemic.

The significant interaction between the post-pandemic period and the negative sentiment variable also indicates that the pandemic negatively moderated the relationship between negative sentiment and ratings. Our review of prior literature implied that COVID-induced changes in the environment prompted customers to be highly alert to and react strongly to service failures (Gerrath *et al*., 2023; Hernández-Maestro *et al*., 2007; McColl-Kennedy and Sparks, 2003; Zhao et al., 2019). However, the results indicate that the pandemic did not significantly moderate the relationship between review length and ratings. This finding might arise because reviews in general grew longer after the pandemic; neutral reviews (majority of the sample) produced after the pandemic were longer than those in pre-pandemic times, for example. Such detailed reviews might reflect consumers' greater sensed need to help others by offering detailed descriptions, even without any negative sentiment. Neutral reviews coincide with average ratings (i.e., not lower than in the pre-pandemic times). Such features of the pandemic atmosphere might undermine the effect we predicted (i.e., moderating effect of the pandemic on the review length–ratings link), even as we confirm a direct negative effect of review length on ratings. On this regard, it has been shown that prosocial behavior, which involves actions that benefit others, develops during adversity, for instance, pandemic times (Tekin et al., 2021). Moreover, social support theory (Cassel, 1976; Cobb, 1976) indicates that social connections and relationships are especially valuable for individuals when facing adversity; in particular, such relationships have been proved to have a positive influence on health and well-being (Lakey and Orehek, 2011; Xin *et al*., 2025). Thus, during the pandemic, individuals are assumed to have a greater need for social support to help offset the negative effects of stress. However, due to the contact restrictions that were in place at the time, online interactions took over and replaced most face-to-face communications. In fact, during 2020, total in-home data consumption grew 18% from 2019 (Comscore, 2021), and socializing with friends and family virtually also increased (GWI, 2020). Thus, writing more detailed reviews would have let individuals feel closer to others, and somehow fulfill the basic need of communicating with others.

Finally, turning to our prediction of a positive moderating effect of hotel quality on the relationship between sentiment and ratings, the lack of support in our sample might stem from its composition. By definition, 4-star hotels adopt and pursue similar quality standards, which might limit the variability of the ratings available in our sample. Notably, we find that ratings in our sample ranged only from 7.4 to 9.4 on average. Samples that include hotels of more widely varying quality might produce different results. Nonetheless, the results show that overall reputation of a hotel on Booking.com benefits the hotel, because hotel quality reduces the negative impact of review length on review ratings. In our study, it seems that participants assimilate their hotel evaluations (review ratings) with the hotel's average evaluations on the platform. We reaffirm this finding when we use the hotel's response as an alternative a proxy of hotel quality, such that it weakens the negative impact of review length on review ratings.

5.1. Theoretical implications

This study extends hospitality research related to review length and review sentiment, by examining not only their direct effects but also some pertinent moderating effects. In particular, the moderating effect of review length emerges as a notable contribution that should inform ongoing research (Geetha *et al.*, 2017; Ghasemaghaei *et al.*, 2018). In a sample of reviews offering negative feedback from Booking.com, we determine that the intensity of the negative sentiment in this feedback relates to lower ratings. Also, the longer the text, the lower the review rating. By further showing that review length moderates and enhances the effect of negative sentiment on ratings, this study offers a valuable insight.

The proposed integrative theoretical framework in turn offers a comprehensive perspective on the influence of review sentiment and length on ratings, encompassing their direct effects but also the moderating influences of review length, social turbulence, and hotel quality. This expansive perspective reflects our effort to integrate multiple theories, including signaling theory (Akerlof, 1970), social sharing of emotions theory (Rimé *et al*., 1992), terror management theory (Greenberg *et al*., 1986), and cognitive dissonance theory (Festinger, 1957). In turn, we demonstrate that theories formulated in the past century, in fields other than consumer behavior (e.g., biology for signaling theory; psychology for cognitive dissonance theory), remain relevant for explaining consumers' behaviors today, in an online context. People still communicate their emotions to others and rate products and services (i.e., hotels), as predicted by social sharing of emotions and signaling theories. The pandemic created anxiety and, as predicted by terror management theory, affected consumers' states of mind, such that they became particularly vigilant, which negatively affected their experience ratings. Finally, we find that customers' experience evaluations are biased by the hotel's reputation and their own expectations, which resonates with cognitive dissonance theory (see also Hernández-Maestro, 2020; Hernández-Maestro *et al*., 2007; Isen, 1987; Proserpio and Zervas, 2017).

5.2. Practical implications

Even if firms provide exceptional service, negative reviews are unavoidable. They also are useful for and trusted by potential consumers (Casaló *et al*., 2015a; Wang *et al.*, 2023) and therefore should be identified and correctly managed. As we show, very negative sentiment differs from moderately negative sentiment in its consequences. Promptly and accurately identifying reviews that contain very negative sentiment can be especially valuable. Reviews that use adjectives, adverbs, or nouns signaling intense negative emotions are related to lower ratings, more so that those that indicate mild negative sentiment. In addition to searching for very negative reviews, hotel managers might monitor for especially long reviews, because they also are likely to contain negative sentiment. If a review is long, the effect of its negative sentiment is likely to be intensified, because in such cases, the reviewer feels compelled to provide a narrative description of the events that led to the low rating and gain understanding from others. Overall then, even if the hotels struggle with limited time and resources, they can leverage length and sentiment criteria in their efforts to manage eWOM.

To facilitate the tasks of searching for negative sentiment, long reviews, and service failures, hotels might rely on AI tools, which also can provide immediate responses that promise to counteract the negative effects of negative reviews. The various AI tools already available for such purposes continue to improve quickly and progressively, suggesting strong possibilities for enhanced analysis and response capabilities (Li *et al.*, 2022; Sharma *et al.*, 2025; Tassiello *et al.*, 2024; Vermeer *et al.*, 2019). In this context, by employing AI review sentiment analysis, hotels could identify service elements and amenities that produce negative emotions, helping them to make better decisions and hence boosting customer experience. Similarly, when applied to examine reviews, AI tools could even detect particular emotions, such as sadness, fear, anger, etc. which would provide a deeper understanding of customers. AI tools can also generate personalized responses that align with the customers' emotions and language. Lastly, apart from reviews, AI-sentiment analysis could be used to monitor social media platforms or news articles, allowing firms to get market insights (e.g. identifying customer trends, detecting negative publicity in relation to an industry or brand). Therefore, companies could implement corrective actions before problems escalate into major issues, counteracting negative effects and preserving brand reputation.

In line with our study results, we also suggest that, in times of crisis and psychological distress, hotels might benefit if they work to allay guests' negative emotional states. In such conditions, consumers' general discomfort can produce lower ratings. We propose that the role of front-desk personnel is especially pertinent in this sense, such that they should be trained to provide warm welcomes and treat clients calmly, then manage the check-out experience carefully. It is advisable to ask guests if they had any problems, to address the concern immediately and thus potentially avoid subsequent, negative online reviews.

Finally, hotels should constantly work to improve their overall service quality and make customers' service experiences as pleasant as possible. Overall service quality (and the resulting reputation) can protect against service failures, such that clients do not penalize service failures by high-reputation hotels as intensely. In support of such efforts, hotel managers should carefully analyze the content of the negative and long reviews they identify, to obtain specific cues and hints about which elements of their service delivery are dissatisfying and need to be improved.

In the course of undertaking these quality improvements, hotels also should respond to the reviews. For our study sample, hotels that responded to negative reviews (versus those that do not respond) exhibited a weaker relationship between negative sentiment and ratings, seemingly because their responses signal care for customers and thus higher overall service quality. For these responses to be effective, they likely need to be timely, to avoid the potential damage to the hotel's reputation as soon as possible. According to prior research, these responses also should address the issue mentioned in the review, offering at least an explanation, and express gratitude (Hernández-Maestro, 2020; Zhang *et al*., 2020).

5.3. Limitations and further research

This study is limited to data from a single booking platform (i.e., Booking.com), and the characteristics of eWOM can vary across platforms. It clearly would be beneficial to include additional platforms in continued research, even though Booking.com represents the greatest share of hotel reviews. In this sense, the strong market position of Booking.com offers confidence in the findings. Furthermore, we only analyzed reviews of 4-star hotels in the Canary Islands, a category that represents more than half of all travelers and beds in Spain. Extending the analysis and testing our proposed framework among a broader classification of hotels remain objectives for continued research. Finally, in its analysis of the review text, NVivo failed to classify some negative sentiments correctly, such as when reviewers used irony. As the development of AI continues, more advanced methodologies (e.g., deep learning) could help refine the sentiment analysis (Li *et al*., 2022; Sharma *et al*., 2025). In parallel, exploring the effect of AI-produced eWOM offers an innovative and potentially fruitful research direction.

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Figure 1. Conceptual model

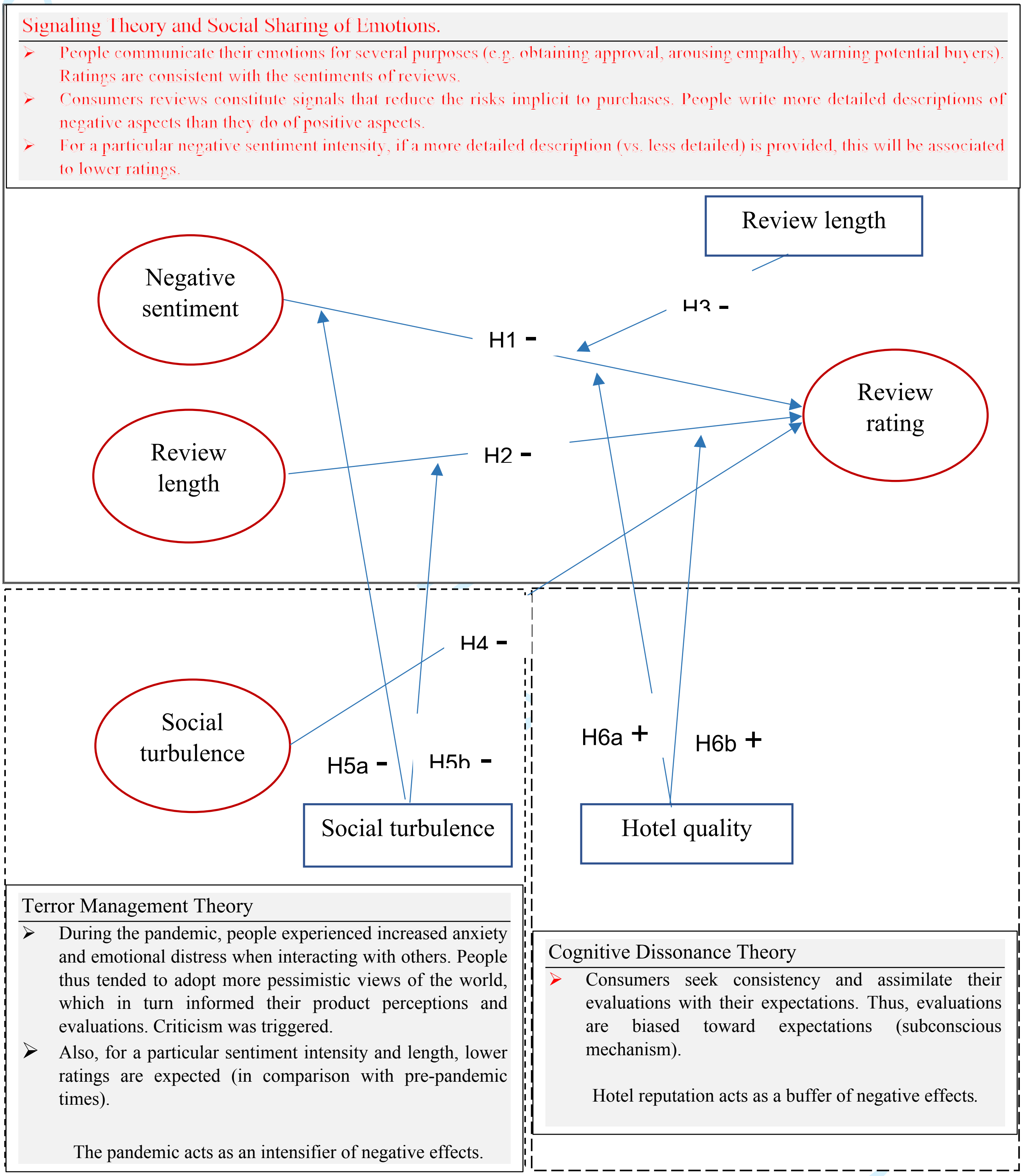


Figure 2. Interaction plots with moderating variables

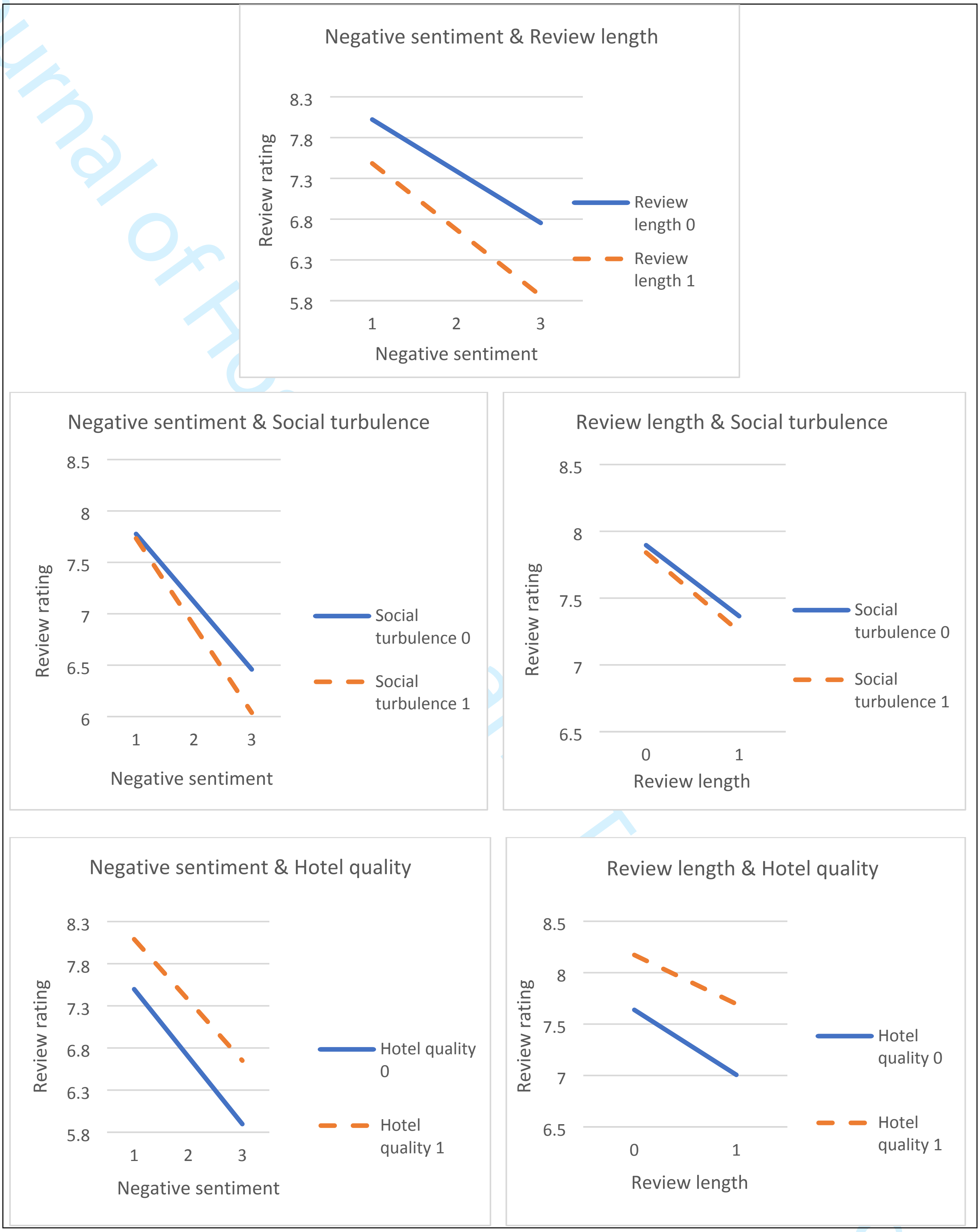


Table I. Summary of relevant prior research

Study	Methodology	Main findings
Verhagen *et al.* (2013)	Survey, telecom providers. Partial least squares (PLS), empirical	Negative eWOM is driven by positive and negative emotions and is strongly predictive of the sender's intended conduct. Positive affect negatively influences negative eWOM; negative affect positively influences negative eWOM.
Xu and Li (2016)	Sentiment analysis of hotels on Booking.com, empirical	Determinants that create customer satisfaction (positive reviews) or dissatisfaction (negative reviews) toward hotels differ and are specific to particular types of hotels (e.g., full-service, limited-service, suite hotels with or without food and beverages).
Geetha *et al.* (2017)	Sentiment analysis of budget and premium hotels, empirical	Sentiment polarity explains variation in customer ratings across hotel categories. Further research is needed to test customer review length's effects on customer ratings.
Ghasemaghaei *et al.* (2018)	Sentiment analysis of insurance services, empirical	Consumer review sentiment correlates positively and review length correlates negatively with online review ratings. Post hoc analyses of the influence of review sentiment and length on ratings (two-way ANOVA) show that, in general (but not in all cases), short reviews with positive sentiment are associated with high review ratings.
Zhao *et al.* (2019)	Sentiment analysis of hotels on Tripadvisor, empirical	Greater subjectivity and readability and longer textual review length lead to lower overall customer satisfaction (customer review rating). More diversity and positive sentiment in textual reviews lead to higher overall customer satisfaction.
Burtch *et al.* (2018)	Empirical	The combination of financial incentives and social norms yields the greatest overall benefit, by motivating more reviews of greater length.
Rohde *et al.* (2022)	Sights on Google Maps and restaurants on Yelp, empirical	Lower ratings relate to longer reviews. More existing reviews decreases the length of a textual review. However, reviewers do not increase their effort if there is a large discrepancy between the existing rating valence and their own rating.
Kim *et al.* (2023a)	Experiment in tourism, empirical	When quality and ethical concerns are prominent, acceptance of and satisfaction with ChatGPT's recommendations decrease significantly. The negative effects were mediated by perceived trustworthiness.
Kim *et al.* (2023b)	Experiment in tourism, empirical	Technology usage experience and ChatGPT's mistakes affect travelers' intentions to use ChatGPT.
Wang *et al.* (2023)	Airline industry on Skytrax, using LIWC, empirical	Negative (positive) sentiment expressed in passengers' online reviews has a negative (positive) influence on their intentions to recommend.
Tassiello *et al.* (2024)	Conceptual	In introducing an aiWOM concept, they call for research into consumers' decision-making process, psychology, new experiences, and AI relationships.

Table II. Sample description: Reviews (N = 19,441)

Variable	Average value *(SD)*	Min.	Max.
Rating	7.62 *(1.99)*	1	10
Nights	3.17 *(2.17)*	1	21
	N	**%**	
Type of company			
Family	5,502	28.3	
Group	1,805	9.3	
Couple	10,889	56	
Alone	1,245	6.4	
Year			
Year 2019	8,245	42.4	
Year 2021	11,196	57.6	

Table III. Sample description: Hotels (N = 121)

Variable	**Average value *(SD)***	**Min.**	**Max.**
Price per person and night	84.26 *(34.20)*	31.33	272.25
Hotel rating	8.31 *(0.41)*	7.40	9.40
	N	**%**	
Hotel quality category			
Fantastic (+ 9)	13	10.7	
Fabulous (8.5–9)	35	28.9	
Very good (8-8.4)	52	43.0	
Good (5–7.9)	21	17.4	

Table IV. Variable measures

Variable	Description and Measure
Review rating	Score assigned by the customer to the overall experience at the hotel (on Booking.com); 10-point scale
Price	Price in € per night and per person for a standard room at the hotel, VAT included, on Booking.com
Food Swimming pool Room Quality Front-desk COVID-19	Dichotomous variables, = 1 if the specific topic is present in the review, and 0 otherwise
Negative sentiment	Negative sentiment intensity: 1 = neutral sentiment; 2 = moderate negative sentiment; 3 = intense negative sentiment
Review length	Dichotomous variable, = 1 if the review length is longer than the median (99 characters), and 0 otherwise
Social turbulence (COVID)	Dichotomous variable: 1 = 2021, 0 = 2019
Hotel quality (average rating)	Dichotomous variable, = 1 if the hotel's average score on Booking.com is above the median (8.4), and 0 otherwise

Table V. Regression model results (N = 19,441; dependent variable: Review rating)

Variable	Regression 1		Regression 2		Regression 3		VIF
	B (p-value)	**Beta**	**B (p-value)**	**Beta**	B **(p-value)**	**Beta**	
Constant	7.229 (0.000)***		8.395 (0.000)***		8.177 (0.000)***		
Price	0.002 (<0.001)***	0.130	0.001 (<0.001)***	0.075	0.001 (<0.001)***	0.074	1.209
Food	-0.571 (<0.001)***	-0.088	-0.402 (<0.001)***	-0.062	-0.395 (<0.001)***	-0.061	1.062
Swimming pool	-0.319 (<0.001)***	-0.041	-0.015 (0.775) n.s.	-0.002	-0.006 (0.909) n.s.	-0.001	1.034
Room	-0.804 (<0.001)***	-0.108	-0.552 (<0.001)***	-0.074	-0.543 (<0.001)***	-0.073	1.037
Quality	-0.830 (<0.001)***	-0.092	-0.369 (<0.001)***	-0.041	-0.363 (<0.001)***	-0.040	1.086
Front-desk	-0.678 (<0.001)***	-0.070	-0.348 (<0.001)***	-0.036	-0.352 (<0.001)***	-0.036	1.042
COVID-19	-0.825 (<0.001)***	-0.080	-0.487 (<0.001)***	-0.047	-0.464 (<0.001)***	-0.045	1.058
Negative sentiment			-0.770 (<0.001)***	0.201	-0.554 (<0.001)***	-0.144	1.116
Review length			-0.564 (<0.001)***	-0.142	-0.424 (<0.001)***	-0.106	1.172
Social turbulence			-0.084 (0.002)***	-0.021	0.150 (0.030)**	0.037	1.058
Hotel quality (average rating)			0.610 (<0.001)***	0.151	0.480 (<0.001) ***	0.119	1.186
Negative sentiment * Review length					-0.166 (0.007)***	-0.067	
Negative sentiment * Social turbulence					-0.182 (<0.001)***	-0.066	
Review length * Social turbulence					-0.023 (0.676) n.s.	-0.005	
Negative sentiment * Hotel quality					0.050 (0.353) n.s.	0.017	
Review length * Hotel quality					0.141 (0.011)**	0.029	
R	0.256		0.393		0.395		
R2	0.065		0.155		0.156		
Adjusted R2	0.065		0.154		0.155		
F	194.530		323.230		224.407		
Sig	<0.001		0.000		0.000		

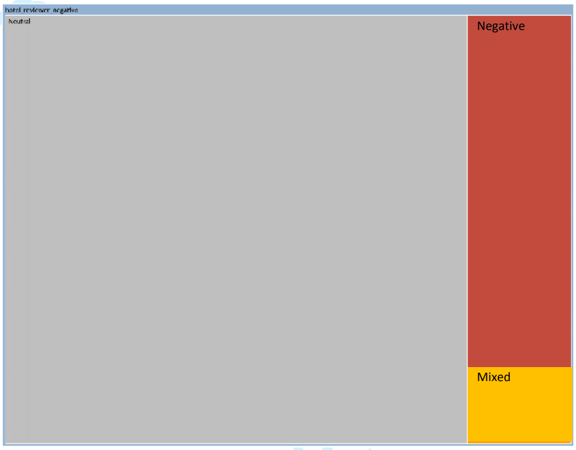
** $p < 0.05$.
*** $p < 0.01$.
Notes: VIF = variance inflation factor.

Table VI. Hypotheses test results

Hypothesis	**Result**
H1. The intensity of the negative sentiment in tourists' online textual reviews negatively affects their review ratings.	Supported
H2. Review ratings are negatively affected by the length of negative online reviews.	Supported
H3. Review length enhances the effect of negative sentiment intensity on review ratings.	Supported
H4. Due to social turbulence caused by the outbreak of the COVID-19 pandemic, tourists' hotel ratings were lower.	Supported
H5. Due to social turbulence caused by the outbreak of the COVID-19 pandemic, the effects of (a) negative sentiment and (b) review length on hotel ratings were enhanced.	H5a Supported H5b Not supported
H6. Hotel quality diminishes the strength of the negative relationships among (a) negative sentiment intensity and ratings and (b) review length and ratings.	H6a Not supported H6b Supported

Appendix I. NVivo output

I.1. Sentiment results



	A : Very negative	B : Moderate negative	C : Moderate positive	D : Very positive
1 : Codes	951	2892	511	182

Note:

The sentence-based NVivo's method has been used. NVivo uses a scoring system based on words, where the score to each word determines the sentiment code it is coded to. The score assigned to each word can change if they are preceded by a modifier (for example, more or somewhat), which intensifies the sentiment. At the same time, sentences may be coded into several categories.

For the purpose of this research, the more negative sentiment code contained within a review has been taken into account when classifying. That is, when a review contains a very negative sentence/code, it has been classified just as a *very negative review* (although it may also contain a *moderate negative sentiment sentence*).

Like most text analysis tools, NVivo cannot recognize sarcasm, double negatives, etc.; context is not considered either. However, to try and increase accuracy, a random selection of reviews (20) for each sentiment category was examined by the researchers, and the results were satisfactory.

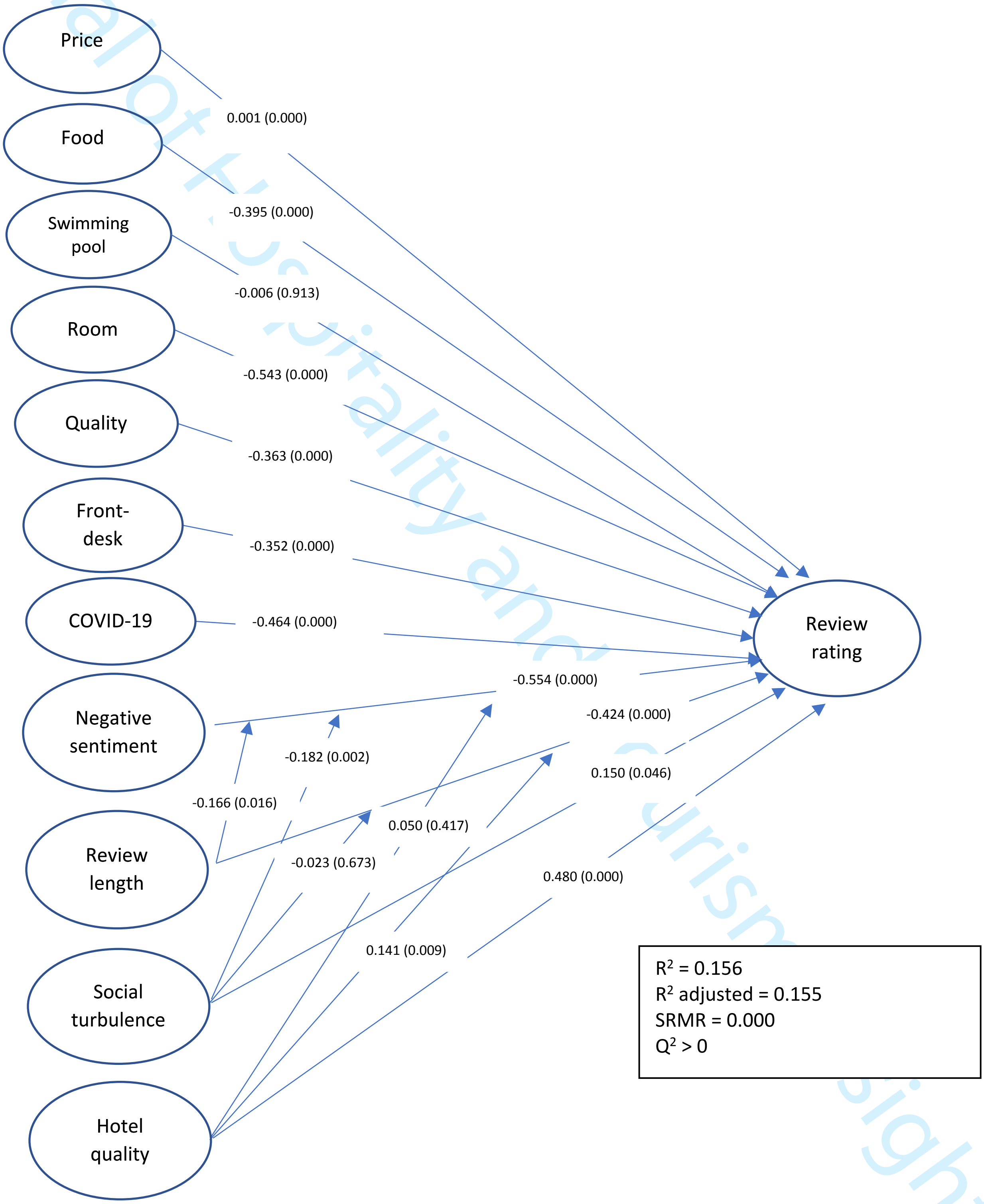
I.2. Themes results. Automatic detection tool.

Word	**Count**	**Weithted percentage (%)**
Food		
Meals	4,032	1.41
Variety	1,708	0.60
Breakfast	1,646	0.57
Buffet	1,642	0.57
Dinner	1,428	0.50
All-inclusive	962	0.34
Drinks	743	0.26
Swimming pool		
Swimming pool	3,180	1.11

Opening times	987	0.34
Hammock	859	0.30
Room		
Room	5,791	2.02
Bed	1,504	0.52
Bathroom	1,187	0.41
Cleaning	1,072	0.37
Shower	604	0.21
Decoration	404	0.14
Manteinance	203	0.07
Quality		
Quality	1,632	0.57
Price	711	0.25
Front-desk		
Personal attention	1,442	0.50
Front-desk	970	0.34
Check-in/check-out	429	0.15
COVID-19		
COVID	624	0.22
Sanitizer	426	0.15
Mask	203	0.07
Pandemic	106	0.04

Appendix II. Additional analyses

II.1. PLS-SEM results. Unstandardized coefficients (p-values). Bootstrapping (5,000 subsamples)



II.2. Separate models (regression) for each moderating effect (N = 19,441; dependent variable: Review rating)

Variable	Regression 3. 1		Regression 3.2		Regression 3.3		Regression 3.4		Regression 3.5	
	B (p-value)	Beta	B (p-value)	Beta	B (p-value)	Beta	B (p-value)	Beta	B (p-value)	Beta
Constant	8.247 (0.000)		8.262 (0.000)		8.380 (0.000)***		8.433 (0.000)***		8.429 (0.000)***	
Price	0.001 (<0.001)***	0.075	0.001 (<0.001)***	0.075	0.001 (<0.001)***	0.075	0.001 (<0.001)***	0.075	0.001 (<0.001)***	0.075
Food	-0.400 (<0.001)***	-0.062	-0.401 (<0.001)***	-0.062	-0.402 (<0.001)***	-0.062	-0.402 (<0.001)***	-0.062	-0.399 (<0.001)***	-0.062
Swimming pool	-0.011 (0.836) n.s.	-0.001	-0.013 (0.810) n.s.	-0.002	-0.014 (0.793) n.s.	-0.002	-0.014 (0.787) n.s.	-0.002	-0.013 (0.805) n.s.	-0.002
Room	-0.548 (<0.001)***	-0.074	-0.549 (<0.001)***	-0.074	-0.551 (<0.001)***	-0.074	-0.552 (<0.001)***	-0.074	-0.550 (<0.001)***	-0.074
Quality	-0.368 (<0.001)***	-0.041	-0.365 (<0.001)***	-0.040	-0.368 (<0.001)***	-0.041	-0.368 (<0.001)***	-0.041	-0.368 (<0.001)***	-0.041
Front-desk	-0.345 (<0.001)***	-0.035	-0.354 (<0.001)***	-0.036	-0.352 (<0.001)***	-0.036	-0.349 (<0.001)***	-0.036	-0.349 (<0.001)***	-0.036
COVID-19	-0.481 (<0.001)***	-0.047	-0.471 (<0.001)***	-0.045	-0.477 (<0.001)***	-0.046	-0.487 (<0.001)***	-0.047	-0.488 (<0.001)***	-0.047
Negative sentiment	-0.634 (<0.001)***	-0.165	-0.659 (<0.001)***	-0.172	-0.770 (<0.001)***	-0.201	-0.800 (<0.001)***	-0.209	-0.768 (<0.001)***	-0.200
Review length	-0.360 (<0.001)***	-0.090	-0.566 (<0.001)***	-0.142	-0.531 (<0.001)***	-0.133	-0.565 (<0.001)***	-0.142	-0.632 (<0.001)***	-0.158
Social turbulence	-0.084 (0.002)***	-0.021	0.146 (0.033)**	0.036	-0.055 (0.145) n.s.	-0.014	-0.083 (0.002) ***	-0.021	-0.083 (0.003) ***	-0.020
Hotel quality (Average rating)	0.610 (<0.001)***	0.151	0.609 (<0.001) ***	0.151	0.610 (<0.001) ***	0.151	0.513 (<0.001) ***	0.127	0.534 (<0.001) ***	0.133
Negative sentiment * Review length	-0.178 (0.004)***	-0.072								
Negative sentiment * Social turbulence			-0.189 (<0.001)***	-0.069						
Review length * Social turbulence					-0.060 (0.267) n.s.	-0.014				
Negative sentiment * Hotel quality							0.080 (0.126) n.s.	0.027		
Review length * Hotel quality									0.155 (0.004)***.	0.032
R	0.394		0.394		0.393		0.393		0.394	
R2	0.155		0.155		0.155		0.155		0.155	
Adjusted R2	0.155		0.155		0.154		0.154		0.155	
F	297.102		297.599		296.400		296.509		297.111	
Sig	0.000		0.000		0.000		0.000		0.000	

** $p < 0.05$.
*** $p < 0.01$.