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Daily Online Review Sentiment and Hotel Performance

Abstract

Purpose – To investigate the links between daily review sentiment and the hotel performance measures of occupancy rate (OR), average daily rate (ADR), and revenue per available room (RevPAR).

Design/methodology/approach – We conducted review sentiment analyses in three moments (-1, -7 and -14 days) before arrival time using a dataset of budget hotel performance and online reviews. Our aim was to identify the effect of review sentiment in the budget hotel market on the three performance metrics.

Findings – Daily sentiment positively affects ADR and negatively affects OR and RevPAR, but only up to a certain threshold, after which the trend reverses. Prices increase with the level of sentiment, and high prices lead to low OR and RevPAR only when the sentiment scores are low. When they are high, they are associated with low rates, which lead to high OR and RevPAR.

Originality/value –We identify daily sentiment as an alternative predictor of hotel performance. In addition to the roles of valence and volume in the decision-making process, we found that daily review sentiment can be an “in-the-moment” factor with a high impact, encouraging consumers to complete their transactions. Our study suggests that aggregated measures such as the total number of reviews and overall ratings of the hotel should not be the sole consideration in reputation management.

Implications – Daily review sentiment can be viewed as a valuable “barometer” indicating a hotel’s daily operational effectiveness. Daily sentiment can thus allow hotel managers to adjust their dynamic pricing strategies more accurately.

Keywords: Online reviews; Daily sentiment; Hotel performance; Revenue management; Social media analytics

Paper type: Research Paper

Introduction

Online consumer reviews are an electronic form of word-of-mouth and have been recognized as an important information source for consumer decision-making, particularly in the context of hospitality and tourism, where products are highly experiential (Sparks and Browning, 2011). The relationships between components of online reviews such as valence, volume, and textual content and performance indicators such as revisit intention, price, number of bookings, occupancy or revenue per available room have been identified (Abubakar *et al*., 2016, 2017; Chang *et al*., 2021; Hu *et al*., 2022; Simonetti and Bigne, 2022; Viglia *et al.*, 2016; Yang *et al*., 2018). The predictability of these relationships depends on contextual factors such as the hotel class and geographical location (e.g., Blal and Sturman, 2014; Phillips *et al*., 2015). Research indicates a strong correlation between online reviews and hotel performance, although this correlation may be influenced by many factors, such as seasonality and external events (Zhang *et al*., 2021; Zhang *et al.*, 2022). Thus, online reviews should be considered when identifying key competitors and can thus help to increase a hotel's competitiveness (Ye *et al*., 2022).

Based on dual-process theory (Evans and Stanovich, 2013), in this study, we investigate the direct links between daily review sentiment and the standard hotel performance measures of occupancy rate (OR), average daily rate (ADR), and revenue per available room (RevPAR). Review sentiment represents opinions extracted from text. The analysis technique involves mining sentiment from a large volume of reviews (Song *et al*., 2020) and has been applied in academia (Chatterjee, 2020; Gkritzali, 2017; Lalicic *et al*., 2021; Zhang *et al*., 2020) and industry. Daily review sentiment is a real-time measure of consumers' evaluations of a hotel property and has been integrated into analytical tools such as IDeaS and TravelClick for hotel pricing and revenue management (e.g., Lennon, 2021; Weed, 2021). Recent studies show that electronic word-of-mouth in general and review sentiment in particular significantly affect consumers' decision-making processes, particularly their willingness to pay or revisit (e.g., Park *et al*. 2020), which influences hotel performance (Phillips *et al*., 2017). Our study addresses limitations in the literature regarding the causal relationship between online reviews and hotel performance, which we describe in more detail later.

Table 1 in the literature review section indicates the two main online review components of volume (measured through the number of reviews) and valence (measured primarily through overall ratings) associated with a specific hotel property, which have been used as predictors of hotel performance. However, establishing causal relationships between the volume and valence of online reviews and hotel performance is both theoretically and methodologically challenging. First, the endogeneity of electronic word-of-mouth means there is a lack of consensus regarding this causal link (e.g., Kim *et al*., 2015; Philips *et al*., 2015; Yang *et al.*, 2018). The two domains of electronic word-of-mouth and hotel performance simultaneously and continuously "feed into" each other (Ampountolas and Legg, 2021).

Thus, we address the following research question: do hotels have good performance because they receive positive electronic word-of-mouth, or do they receive positive electronic word-of-mouth because they have good performance? However, establishing a definitive answer to this question is challenging. In addition, volume and valence represent heuristic cues that signal a hotel's reputation and guest satisfaction (e.g., Liu and Park, 2015; Purnawirawan *et al*., 2015). Reviews accumulate over the lifetime of the brand or property after it first appears on a review site or distribution platform. However, in addition to their potential endogeneity in terms of hotel performance, reviews do not necessarily reflect consumers' real-time evaluations of their hotel experiences or the time-sensitive nature of making a hotel booking.

Thus, we argue that daily consumer sentiment derived from individual review texts is an appropriate measure of the true impact that these reviews have on hotel performance. We therefore operationalize daily review sentiment as consumer sentiment derived from the textual content of online reviews on a specific day for a specific hotel property. This measure has two main benefits. First, unlike review volume (which can increase with sales and occupancy), sentiment in individual reviews can indirectly affect occupancy through satisfaction. As Aakash and Aggarwal (2022) note, review sentiment reflects "the level of satisfaction in terms of positive, negative, or neutral sentiments that customers represent by posting eWOMs. (p. 321)" Thus, a consumer may write a positive (negative) review because he/she is satisfied (dissatisfied) with the hotel stay, not directly because of the hotel's occupancy rate (although these factors could be inherently connected).

Thus, endogeneity will be less of a problem if we model the impact of online reviews on hotel performance using daily sentiment as the predictor (although we address potential endogeneity in our analysis). Second, compared to overall rating, which is the average of the individual review ratings over a hotel's lifetime, sentiment offers a more fine-grained view of consumers' evaluations of the hotel and their experiences. Using individual review sentiment to gauge the impact of online reviews on hotel performance is a flexible approach, as it can, for example, be aggregated over different periods to elicit time-dependent and time-sensitive inferences about hotel performance.

The goal of this study is therefore to evaluate the influence of daily review sentiment on the hotel performance indicators of occupancy rate (OR), average daily rate (ADR), and revenue per available room (RevPAR). Our two objectives are as follows. First, we seek to confirm that daily sentiment is positively correlated with a hotel's operational performance and that review sentiment is highly correlated with rating, which is a strong predictor of hotel performance. Second, although these widely used hotel performance indicators are interrelated, they reflect a hotel's response to the market differently (Schwartz *et al*., 2017). For example, the OR is a direct reflection of hotel sales, which although conditioned on the rates set through revenue management strategies may be directly correlated with review sentiment. However, the ADR is based on the daily price as (presumably) set by the hotel's revenue manager and is therefore fully controlled by the hotel.

Thus, based on these assumptions about the relationships between review sentiment and hotel performance and the differences in what OR, ADR, and RevPAR reflect in terms of performance, we address two main research questions:

Q_1: *To what extent does daily review sentiment predict daily hotel performance?*

Q_2: *Does the impact of daily review sentiment vary across different hotel performance indicators?*

Dual-process theory, which refers to the duality of deliberate thinking (systematic processing) and intuitive thinking (heuristic processing), provides a theoretical basis for describing the influence of user-generated content on sales. Review sentiment can be regarded as a form of systematic processing (Wang *et al.*, 2022). We conduct our review sentiment analyses at three different moments (-1, -7, and -14 days) before arrival time. This enables us to identify the effect of review sentiment on ADR, OR, and RevPAR in the budget hotel market. We focus on budget hotels because their customers tend to be less loyal and thus more likely to rely on online reviews when making their reservations, which they typically do in short time windows (Lei *et al*., 2019). Measuring sentiment scores over several time moments can reveal potential differences in the effects of these scores on performance.

Literature Review

An online hotel review can be regarded as a bundle of information that reflects a consumer's evaluation and experience of a specific hotel and that may elicit interest and responses from the online community and the hotel company (Xiang *et al*., 2017). The formats of online reviews differ according to the platform, but they typically consist of several informational components, including linguistic characteristics, content (meaning), sentiment (emotional aspects of the content), ratings, peripheral cues such as source (information about the reviewer), feedback such as a helpfulness score, and possibly managerial responses (Xiang *et al*., 2017; Xie *et al*., 2017).

The effects of these components on consumers' perceptions of the informational value of the review can vary. They may affect how consumers regard the hotel product when searching for information or decision-making (e.g., making a reservation) (Sparks and Browning, 2011). For example, in terms of linguistic characteristics, the readability and length of reviews can have an effect on its perceived usefulness, and its textual content can inform the reader about the reviewer's direct experiences with various attributes of the hotel (Xiang *et al*., 2015). Other content- or non-content-related cues, such as the reviewer's personal information, may serve as measures of the review's authenticity and trustworthiness (Park *et al*., 2014).

Recent studies of the hospitality industry identify positive relationships between various aspects of online reviews and direct and indirect hotel performance measures. They consider online reviews as a source of factors that contribute to business performance and highlight the need to improve product quality and effectively manage online reputation and customer engagement (e.g., Xiang *et al*., 2015). Table 1 provides a list of 23 representative studies, organized chronologically, that consider the direct linkage between online reviews and hotel performance. This list includes empirical studies that consider valence and volume as predictors of hotel performance. The list also illustrates the development of this stream of literature from its outset (i.e., Ye *et al*., 2009) to the present. Table 1 also gives the variables used in the analyses, the analytical methods and main findings, and the citations.

[Table 1 about here]

Over the past ten years, interest in the effects of online reviews on hotel performance has increased. The two main online review components that are regarded as predictors of hotel performance measures (as seen in Table 1), with some variations, are the volume of reviews and valence (measured primarily by overall ratings) associated with a specific hotel property. Over half (11) of these studies use both components simultaneously, while others consider only one. Other review-related factors are included in several of these studies, such as review quality (e.g., Duverger, 2013; Mariani and Borghi, 2020; Viglia *et al*., 2016; Xie *et al*., 2014; Xie *et al*., 2014) and managerial responses to reviews (e.g., Kim *et al.*, 2015; Raguseo and Vitari, 2017; Xie *et al.*, 2017).

ADR, occupancy, and RevPAR are the most frequently used measures of hotel performance. Other hotel performance measures are also used, such as number of days booked (Brandes *et al*., 2011), RevPAR growth and the sales profitability differential (e.g., Raguseo and Vitari, 2017), and the number of reviews (e.g., Ogüt and Onur Tas, 2012; Ye *et al*., 2009). The control variables used in these studies are diverse, and mainly include hotel attributes such as type, class, brand, amenities, size, and geographic location (e.g., Kim *et al.*, 2015; Philips *et al*., 2015) as well as variables associated with hotels' marketing and operations (e.g., de Pelsmacker *et al*., 2018; Mariani and Visani, 2019). In general, most studies use regression-based analytical methods to test the relationships between review-related variables and hotel performance measures, demonstrating that review valence is a stronger predictor of hotel performance than review volume.

However, in the hospitality literature, these predictors of hotel performance do not reflect the decision process indicated by dual-process theory, which guides our study. This cognitive psychology theory considers how distinct procedures are used to arrive at decisions, such as “systematic processing” (which entails a rational examination of content such as review sentiment) and “heuristic processing” (intuition-based decisions based on star ratings or review volume) (Wang *et al.*, 2021). Dual-process theory describes how information such as online reviews is considered, processed, and evaluated (Chakravarti *et al.*, 1997). The theory also provides a critical theoretical foundation for describing—beyond the way people make online decisions—the effect of user-generated content on sales, particularly in terms of systematic processing as revealed by review sentiment (Wang *et al.*, 2022). Yin *et al.* (2016) point out that review sentiment is crucial in signaling the quality of a product and its value and thus affects sales (Fan *et al.*, 2017; Lee *et al.*, 2017).

Review sentiment and rating both reflect the valence of a specific review (Chatterjee, 2020; Sparks *et al*., 2013). An individual reviewer’s rating is a numeric evaluation of the product and of actual experience, and indicates the level of satisfaction with a specific property or business (Park and Nicolau, 2015; Xiang *et al*., 2015). While sentiment broadly refers to consumers’ opinions of a product (Feldman, 2013), within the context of online hotel reviews, it is generally defined as a measure of their evaluative responses (i.e., positive vs. negative) to their experiences of a hotel stay, as inferred from the textual content of the reviews, usually via machine learning tools (e.g., Chatterjee, 2020; Xiang *et al*., 2017). Review sentiment thus reflects the valence of opinion, which can be inferred from the textual content of the review (Pang and Lee, 2008).

Although the manipulation of online reviews can lead to anomalies (e.g., Schuckert *et al*., 2016), review sentiment and the ratings assigned to a hotel property are inherently connected, as a positive sentiment in the review text should be congruent with the numeric score assigned to the property by the individual review, as recent empirical research shows. The overall rating of a specific hotel is the average of all reviewers' ratings and thus captures the overall sentiment exhibited in all reviews accumulated through the lifetime of the property since it first appeared on the review platform (Xiang *et al*., 2017).

The construction of individual review sentiment and overall hotel rating suggests that their effects on consumers' decision making and, consequently, hotel performance are likely to differ. They generally provide "fast and easy" cues, and as Park and Nicolau (2015) demonstrate, polarized reviews in terms of ratings can lead to higher perceptions of usefulness and enjoyment in consumers, as they are less ambivalent, more informative, and easier to process than other reviews. When faced with information overload, many people resort to heuristics. However, consumers can take a step further, reading and processing the information contained in reviews, so they can confirm or gain a better understanding of what is actually involved in a rating. One study finds that over 90% of consumers read at least one review before purchasing (Spivack, 2019), and Kim (2008) states that nearly 70% of retail consumers read at least four reviews before making a purchase. Other reports suggest that consumers spend considerable time reading reviews before making a purchase decision (Bright Local, 2020).

Considering the experiential nature of the hotel product and the high risk involved, consumers are likely to pay more attention to the content and thus the associated sentiment in relevant online reviews. The sentiment manifested through the textual content of a review, i.e., the extent to which the opinion is positive or negative, will likely affect the consumer in a similar way to the overall rating, although it will not be exactly the same.

Factors such as seasonality and service quality variability in the hotel industry are also likely to prompt consumers to assign relatively more weight to more recent reviews, i.e., those closer to the time of booking. Recent trends in consumer behavior, as reflected in the so-called "deal seeking" culture (Webb *et al*., 2020), also suggest that they are likely to research products before making last-minute decisions and purchases. Recent reviews will then exert a higher effect on a consumer's imminent booking intention (Liu and Beldona, 2021) and hence a hotel's daily operations and performance. The extent to which consumers use and interpret recent reviews has received limited empirical attention, but the importance of such reviews is reflected in the designs of many booking websites. They typically incorporate review contribution date as a sorting option for individual reviews. Figure 1 gives a screenshot from the Chinese review and booking app Meituan, in which the circle on the right highlights the function "sorting by review time."

[Figure 1 about here]

In this study, we argue that daily review sentiment offers a fine-grained, near-real-time measure and has several advantages over the widely used review volume and valence measures. Our research design and analysis make two main contributions: 1) given the generally established positive relationship between review valence and hotel performance, we further explore whether such relationships exist at the daily operational level, and 2) we examine whether the effects of reviews on hotel performance are consistent across different performance indicators (i.e., OR, ADR, and RevPAR). This study therefore provides a more nuanced understanding of the impact of online reviews in consumers' decision-making processes, and consequently on hotel performance, than valence and volume, as daily review sentiment can better reflect the time-sensitive nature of the hotel service. We also offer insights for online reputation management and hotel revenue management practices.

The data and analytical methods used also contribute to the literature. Unlike many studies that use hotel performance data at the aggregate level, in our analysis, we use actual, property-level daily performance data over 2017, collected from a sample of budget hotels located throughout China. The hotel selection was based on the premise that their consumers are less loyal to brands and so online reviews are important to them when making their booking decisions, usually within a short time window (Lei *et al*., 2019). The hotels were primarily marketed through a popular online booking channel (which remains anonymous to protect its proprietary information) in China. Online review data were collected from the platform and its smartphone app. We use regression-based empirical models to measure the effects of daily review sentiment on the three performance measures, along with several control variables. In the statistical model, we are careful to account for any endogeneity and therefore achieve good causality measures given the limitations of the data. Thus, we are able to demonstrate the effect of online reviews on hotel performance at the daily level.

Methodology

Data

We collected hotel performance data from the database of a property management system supplier and hotel review data from a mobile app that markets travel products in China. The cloud-based property management system is supplied to budget hotels in China, and its database contains all of their transaction data. We were able to access the database and data, for research purposes only, through a collaborative scheme between the institution of one of the researchers and the property management system supplier. The data retrieving process was closely monitored by the supplier's management team. For the purpose of this study, the researchers randomly selected 100 budget hotels out of the 15,000 in the database and obtained their daily transaction data from January 1 to December 31, 2017. The dataset included the following variables: hotel name; booking date; day of week (Monday through Sunday); booking channels, including Channel 1 (the mobile app of the distribution company), Channel 2 (the company's WeChat mini-program), and Channel 3 (its mobile website); daily room revenue; and average daily revenue (ADR). A total of 49,835 transaction records were retrieved for the selected 100 hotels.

A crawling program written in the Python language was used to scrape the daily online reviews of the hotels through 2017 via the smartphone app Meituan, which is the booking channel used. Meituan has now surpassed Ctrip as the most-used app for budget hotel booking in China. Budget hotels now find it too costly to compete for a presence in Ctrip's search results (Soo, 2019). Out of the 100 sampled hotels, we identified online reviews for only 80 during the period, possibly because some are very small businesses. We collected a total of 8,877 reviews, with approximately 111 on average for each hotel. This gives one review every three days, which means that a review will appear at the top of the list for three days on average. Thus, the short time windows that the customers use can be considered. They typically book late and very close to the arrival day, so reviews posted close to their check-in date will be the most read.

Sentiment analysis was then performed to develop an aggregate sentiment score for each hotel's reviews. We followed the standard sentiment analysis procedure outlined by Pang and Lee (2008) and used the Natural Language Toolkit (NLTK) in Python 3 in combination with SnowNLP, a module that deals with Simplified Chinese, for data preprocessing, tokenization, normalization, and sentiment analysis. For each review, we assigned a score within a range of 0-100 and then calculated the mean score of daily sentiment for each hotel on a specific day. Table 2 shows that the average daily sentiment score was 71.5, suggesting that the hotel reviews were generally positive, which is consistent with studies that suggest hotel reviews are skewed toward the positive (e.g., Xiang *et al.,* 2017).

[Table 2 about here]

Table 3 lists all of the variables considered. The dependent variable "budget hotel performance" was measured by occupancy rate (OR), average daily rate (ADR), and total room income divided by total number of rooms (RevPAR). The independent variables included daily sentiment score (sent), with booking channels (Channels 1, 2, and 3), ADR, weekend, and days in operation as control variables. Each channel may attract customers to different degrees, so we included channels because they may influence the hotels' performance metrics. We included weekend as a variable to capture potential weekly changes by comparing weekdays and weekends. Finally, days in operation reflects the hotels' experience in terms of revenue management, which can influence their performance metrics.

[Table 3 about here]

Empirical models

The sentiment variable ("sent") represents the daily sentiment score of a specific hotel property. Its effects on OR, ADR, and RevPAR were measured in three time periods (day -1, day -7, and day -14) by using regression analysis. The empirical models were formulated as follows:

$$\ln(OR_{i,t}) = \alpha_{OR} + \beta_{1OR} \cdot Sent_{i,t} + \beta_{2OR} \cdot Sent_{i,t}^2 + \gamma_{OR} \cdot ADR_{i,t} + \sum_{g=1}^{G} \delta_{gOR} \cdot CV_{ig} + u_i + \varepsilon_{i,t,OR} \quad (1)$$

$$\ln(ADR_{i,t}) = \alpha_{ADR} + \beta_{1AD} \cdot Sent_{i,t} + \beta_{2ADR} \cdot Sent_{i,t}^2 + \sum_{g=1}^{G} \delta_{gADR} \cdot CV_{ig} + u_i + \varepsilon_{i,t,ADR} \quad (2)$$

$$\ln(RevPar_{i,t}) = \alpha_{RevPar} + \beta_{1RevPar} \cdot Sent_{i,t} + \beta_{2RevPar} \cdot Sent_{i,t}^2 + \gamma_{RevPar} \cdot ADR_i + \sum_{g=1}^{G} \delta_{gRevPar} \cdot CV_{ig} + u_i + \varepsilon_{i,t,RevPar} \quad (3)$$

where α is the constant term (different for each OR, ADR, and RevPAR model); β_1 is the coefficient that reflects the effect of the variable "sent" and β_2 reflects the quadratic impact of sentiment; γ is the parameter related to the effect of ADR; δ is the coefficient that shows the effect of the *g-th* control variable CV_{ig} (channel type, weekend, and age); u_i is the hotel's fixed effect; and $\varepsilon_{i,t}$ is the error term that follows a normal distribution. Note that Models 1 and 3 included ADR as an additional independent control variable, as the price of a hotel room is a fundamental variable when estimating or predicting the demand.

Correlation between the variable "sent" and the error term can exist in Equations 1, 2, and 3, as although we hypothesize that *sentiment* can affect the performance metrics (OR, ADR, and RevPAR), the metrics can also influence sentiment, with the variable ADR representing the room rate in Equations 1 and 3. Therefore, any potential endogeneity of the variables "sent" and ADR must be controlled. Thus, we applied Gaussian copulas, in line with (Park and Gupta, 2012). For the variables sentiment (*Sent*) and room rate (*ADR*) the copula terms are obtained as

$$Sent_i^c = \emptyset^{-1}[H_{Sent}(Sent_i)]$$

$$ADR_i^c = \emptyset^{-1}[H_{ADR}(ADR_i)]$$

where the inverse of the cumulative normal distribution is represented by $\emptyset^{-1}$ and $H_{Sent}(Sent_i)$ and $H_{ADR}(ADR_i)$ are the empirical distribution functions of *Sent* and *ADR*, respectively.

This method requires that the regressor that may be endogenous should not be distributed as a normal distribution (Park and Gupta, 2012). Significant parameters for the copulas indicate endogeneity, so they must be included in the estimation. We followed the two-stage procedure of Mathys *et al*. (2016). In the first stage, both copulas for *Sent* and *ADR* are estimated, and in the second, we retained the significant copulas terms to present the endogeneity-corrected estimates.

Before estimating the models, we assessed whether collinearity between the independent variables was an issue. The variance inflation factors (VIF) indicated that all of the parameters were below the recommended value of 10 (Neter *et al*., 1989) (see Table 4), and thus, collinearity did not appear to be an issue. We detected heteroskedasticity by computing the White heteroskedasticity-consistent standard errors using the Breusch–Pagan test (with p-values lower than 1% in all three equations).

[Table 4 about here]

Results

Table 5 shows the main results of the analysis. We tested nine models to estimate the impact of daily review sentiment on the three hotel performance indicators. We first tested the significance of the copula terms to identify those to be introduced into the final models, following Mathys *et al*. (2016). The two-stage procedure considers potential endogeneity (the models estimated in the first stage are not presented here but are available from the authors upon request). Before estimating the copulas, we tested the non-normality of potentially endogenous regressors. The Jarque–Bera test confirmed that the variables *Sent* and *ADR* did not follow a normal distribution ($JB_{Sent} = 341.7$; $p < 0.01$ and $JB_{ADR} = 11966.7$; $p < 0.01$, respectively).

Models 1, 2, and 3 show the effect of time-lagged sentiment scores (-1, -7, and -14, respectively) on ADR; Models 4, 5, and 6 show the effect on OR; and Models 7, 8, and 9 show the effect on RevPAR.

The parameter estimates indicated that the variable *sent* was significant and positive in Models 1, 2, and 3, indicating that sentiment had a positive effect on ADR. The same result was obtained for all the time lags, suggesting the robustness of the tests. We found significant and negative parameters for the quadratic term of sentiment. We combined the linear and curvilinear effects across the range of variable sentiment (0-100) and observed a diminishing sensitivity pattern with an inverted U-shape (see Figure 2). This indicated that the effect of sentiment was increasingly positive up to a point but from then on it diminished. We observed the same robustness over the three time-lags for OR and RevPAR for the sentiment score, with a reverse sign (see Models 4-6 and 7-9, respectively). The parameters were negative and significant for the sentiment score and positive and significant for the curvilinear term. Increases in the sentiment score in the low range indicate that a positive effect from the score on OR or RevPAR only emerged after a threshold.

Increases in sentiment appear to prompt managers to raise rates, but this is combined with reductions in OR and RevPAR. However, this does not occur over the entire range of the sentiment score, and high scores appear to be linked to low rates in budget hotels, increasing OR and RevPAR. This finding supports the results obtained by Abrate *et al*. (2021).

[Table 5 about here]

[Figure 2 about here]

In terms of the control variables, the distribution channels were significant and negative in the OR and RevPAR models but not in the ADR models (Models 1-3). The effects of Channels 1 and 2 were thus significantly lower than that of Channel 3, which was the baseline variable. Although the specific channel does not appear to influence the hotel's rates (they appear to comply with the rate parity agreements), managers should be aware that Channel 3 is more effective at attracting customers than the other two channels.

The variable weekend had a significant and positive effect on the three metrics, but days in operation (the length of time the hotel had been in operation) only had significant and negative effects on OR. The lack of an influence on ADR and RevPAR implies that hotels improve their management of revenue as they gain experience: they keep their levels of RevPAR without necessarily increasing OR.

Discussion with existing literature

In general, our findings support those of other studies that suggest a positive relationship between online reviews and hotel performance (Yang *et al*., 2018). The observed positive effect of sentiment scores on RevPAR after a threshold suggests that daily sentiment inferred from online reviews can, like volume and valence, indicate consumers' reactions to and evaluations of their experiences with the hotel product through electronic word-of-mouth. Thus, our findings further confirm the connections between electronic word-of-mouth and performance in the hospitality business, which supports the conclusions in the literature since the pioneering study by Ye *et al*. (2009). However, our findings are distinct in several areas.

First, unlike other studies, we reveal that online review sentiment has a positive impact on hotel performance at the daily level. Recent economic conditions and the increased use of technology such as smartphones have led to reduced booking windows (Webb *et al*., 2020), and thus the increasing number of travelers making last-minute purchase decisions are more likely to use daily review sentiment as a decision cue alongside overall rating (valence). This is also consistent with the growing interest in and close monitoring of the consumer sentiment reflected in online reviews (e.g., Pelsmacker *et al*., 2018).

Second, this study is consistent with others that demonstrate that consumer interpretations of the valence of reviews, as measured by the overall rating of the business, follow a non-linear rather than a linear pattern (Lai *et al.*, 2021; Li *et al*., 2022; Shin and Nicolau, 2022). Others (e.g., Bridges and Vásquez, 2018) show that extremely positive reviews could be interpreted by consumers as less meaningful than those giving lower ratings, although they represent important informational cues. Sharma *et al*. (2020) suggest that consumers' sensitivity to positive review sentiment diminishes over time. Our findings of differing effects of sentiment on the three metrics are due to the following reasons. Low levels of sentiment initially have minor effects on ADR, OR, and RevPAR, but rates increase with sentiment, which causes a reduction in OR and RevPAR. Only after the effect of sentiment on ADR reaches its maximum are greater levels of sentiments associated with lower rates, which then drive up OR and RevPAR. Revenue managers are likely to consider sentiment when setting rates (Ferguson and Smith, 2014), so as a hotel gains popularity, its rates go up. However, revenue management approaches and price optimization techniques (Vives *et al.*, 2018) suggest that as budget hotels desire to become more popular, i.e., increase sentiment, they are likely to reduce their rates, as otherwise, customers will not respond positively in the longer term.

In Figure 2, the lines showing the effects of sentiment on ADR and OR intersect, indicating that after a certain level of sentiment, the popularity of the hotel is driven by a marginal effect in occupancy that is greater than the marginal decrease in rates. As Leoni *et al.* (2020) find, OR can be less sensitive to price changes but more sensitive to online reviews. The intersection between the marginal effects of sentiment on ADR (negative) and RevPAR (positive) indicate their economic value. From a managerial viewpoint, once the objective of RevPAR is set, these marginal effects can help determine the ideal sentiment to be attained to ensure the expected effect on RevPAR.

Conclusions and Implications

The aim of this study is to examine the relationships between daily review sentiment, as derived from the textual content of online reviews, and hotels' operational performance in terms of OR, ADR, and RevPAR. Our empirical analysis reveals that daily sentiment generally has a positive impact on ADR and a negative impact on OR and RevPAR, and that these positive and negative effects reverse after a specific threshold. Although rates increase with the level of sentiment, as expected, higher prices lead to low OR and RevPAR when the sentiment scores are relatively low. When they are high, they are associated with low rates, which lead to high OR and RevPAR, also as expected (particularly in budget hotels).

Theoretical implications

Our study is based on dual-process theory, which suggests that decisions are arrived at via two procedures. Thus, we consider the distinction between "systematic processing," which entails a rational examination of online content (such as review sentiment) and "heuristic processing," which implies decision-making based on intuition (such as star ratings or review volume). This theory can be useful when assessing the effect of user-generated content on sales, particularly in terms of the systematic processing of review sentiment (Wang *et al.*, 2022). Essentially, review sentiment sends signals into the world about the quality of a product and its value, and thus has an effect on sales (Fan *et al.*, 2017; Lee *et al.*, 2017; Yin *et al.*, 2016). However, the current hospitality literature mainly reflects heuristic processing, and considers volume (number of reviews) and valence (overall ratings) as the two main online review components for predicting hotel performance. We contribute to the literature by conducting review sentiment analyses in three different moments (-1, -7, and -14 days) before arrival time. We can thus identify the effects of review sentiment on the three performance metrics of ADR, OR, and RevPAR in the budget hotel market.

Theoretically, our study makes two main contributions to the understanding of the relationship between online reviews and hotel performance. First, the correlation between daily review sentiment and hotel performance shows empirical evidence that the impact of online reviews is time-dependent (e.g., Jin *et al*., 2014). Although we can reasonably assume that consumers will carefully examine the content of online reviews before making a purchase decision, the literature does not offer explicit evidence of this.

Valence and volume are certainly important measures of guest satisfaction and hotel reputation, and consumers use them as decision cues during the purchasing process (Liu and Park, 2015; Yang *et al*., 2018). However, they both have inherent limitations, as they may not reflect the time-sensitive nature of the hotel service and decision-making. We argue that daily sentiment has several advantages over volume and valence, primarily that endogeneity is less of an issue when assessing the potentially causal relationships between electronic word-of-mouth and performance. However, we were careful in the empirical analysis to statistically address the potential hazards caused by endogeneity.

To some extent, valence and volume can be considered as signaling the general reputation of a hotel and are likely to be factored in during the decision-making process. However, daily review sentiment can be viewed as an “in-the-moment” factor with a higher impact, as it can prompt a consumer to complete the transaction. We offer a fresh perspective on the multi-faceted and multidimensional nature of online reviews within the hospitality context. The novelty of this study thus lies in its research design, which enabled us to "zoom in" and examine the impact of online reviews at the daily level. We therefore identify daily sentiment as an alternative predictor of hotel performance.

Second, we find that daily review sentiment had a non-linear relationship with hotel performance. In general, glowingly positive electronic word-of-mouth does not lead to trust and is not necessarily more persuasive than reviews that offer concrete and nuanced descriptions (Kupor and Tormala, 2018). The online review space has become a complex and dynamic locale where various stakeholders and "players" participate in ongoing conversations with different agendas (Mehraliyev *et al.*, 2022). Within this context, consumers are likely to be aware of the potential manipulation of online reviews and have learned to process and interpret electronic word-of-mouth with caution (Wu *et al*., 2020; Xiang *et al*., 2018). Thus, we highlight the importance of review content, and particularly the sentiments articulated, in constituting meaning and power of persuasion within the hospitality context.

Practical implications

Online reviews no longer consist solely of consumer-generated content but are the direct products of the interactions between online consumers and hospitality businesses. From the business perspective, online reviews can be used to detect real-time market signals and meaningful relationships that inform operational decisions, and they can also be regarded as opportunities for reputation management and customer engagement. In practical terms, hoteliers and managers should be aware that online reviews are not valuable only as spaces for customer engagement and reputation management (Xie *et al*., 2014). Daily review sentiment can be viewed as a valuable "barometer" indicating a hotel's daily operational effectiveness. Reputation management should not be driven solely by aggregated measures, as represented by total reviews and overall ratings of the hotel.

The correlation identified between hotel rates and sentiment scores suggests that online reviews can be used to develop real-time market intelligence to inform hotel operational decisions, particularly in terms of revenue management. Pricing decisions are one example, which we identify as determined in part by daily review sentiment. Revenue managers closely monitor daily sentiment and adjust the hotel's pricing strategy accordingly. They can also benefit from analyzing the sentiment in the reviews of their competitors to determine their price evolution strategies if they know that these rivals also use review sentiment to modify their prices. Daily sentiment can thus allow hotel managers to adjust their dynamic pricing strategies more accurately.

Limitations and future research

This study has several limitations. First, although the hotel daily performance data enabled us to identify the relationships between electronic word-of-mouth and performance in hotels, we only examined a specific market segment (i.e., budget hotels) from a specific national (and perhaps unique) market throughout 2017. The findings should therefore be interpreted with caution. They may not be generalizable to segments such as luxury hotels, whose customers may not rely as heavily on online reviews when making purchasing decisions. Future research can use more comprehensive data or conduct comparative analyses between market segments to establish whether these relationships hold. Comparisons between pre- and post-COVID-19 periods can also reveal potential differences in customers' behavioral outcomes. However, as budget hotels are characterized by most of their bookings being made close to the arrival date, this reflects the trend of making reservations at short notice, which is one consequence of COVID-19.

Second, booking data can indicate when customers make their reservations and when they may read reviews. Sentiment scores do not necessarily vary on a daily basis, and thus, the information available when booking, even if a few days in advance, may be similar to that given on their arrival day. Access to the reservation dates would, however, increase accuracy. The sentiment scale proposed by Mehraliyev *et al*. (2020) can also enable future analyses of different sensory dimensions and assessments of their effects on performance. Finally, the curvilinear relationship between daily sentiment and hotel performance should be tested with more generalizable data to confirm the socio-psychological bases of consumers' responses to online review valence. Nonetheless, our exploration of a new dimension of online hotel reviews offers several directions for future research. This can provide a deeper understanding of the nature and value of electronic word-of-mouth in the hospitality and tourism context.

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Tables and Figures

Tables

Table 1. Representative literature on online reviews and hotel performance

No.	Online review measures			Hotel performance measures	Contextual or control variables	Data analytical technique	Reference
	Valence	Volume	Other				
1	Review score	-	-	N of reviews	-	Log-linear regression	Ye et al. (2009)
2	Review score	N of reviews	-	Number of days booked	Social distance; hotel class; country; meal; time	Log-linear regression	Brandes, Nolte, & Nolte (Lechner) (2011)
3	Online reputation score	N of reviews	-	RevPAR and occupancy	Hotel class	Logistic regression	Anderson (2012)
4	Review score	-	-	N of reviews by N of rooms	-	Regression with OLS	Ogüt and Onur Tas (2012)
5	Review score	-	Review length	RevPAR	Location; hotel class; market related variables	Linear regression	Duverger (2013)
6	Review score	N of reviews	-	RevPAR	Hotel class	Hierarchical linear regression	Blal & Sturman (2014)
7	Rating	N of reviews	Review variance	Hotel sales	Hotel class	Diff-in-Diff based on linear regression	Lu, Ye, & Law, (2014)
8	Review score	N of reviews	Review variation	RevPAR	Variation, management response, size, segment	Linear regression	Xie et al. (2014)
9	Review rating (quality)	N of reviews	Consistency	ADR	Hotel class; amenity; age; size	Log-linear	Xie, Chen & Wu (2016)
10	Overall rating	N of reviews	Managerial response; standard deviation of rating	ADR; RevPAR	-	Linear regression	Kim et al. (2015)
11	Aggregate score	N of reviews	-	RevPAR	Region, class, Size, etc.	Multiple regression; neural networks	Phillips et al. (2015)
12	Review score	N of reviews	Review variance	Occupancy	-	Linear regression	Viglia et al. (2016)
13	Review score	N of reviews	Managerial response	RevPAR growth; Sales profitability differential	Brand; chain	Linear regression	Raguseo & Vitari (2017)
14	Rating	Volume	Managerial response to reviews	Revenue; ADR; Occupancy	Hotel class; amenity; age; size	Linear regression	Xie et al. (2017)
15	Sentiment by hotel attributes	-	-	Occupancy; RevPAR	-	PLS-PM	Phillips et al. (2017)
16	Guest experience index (GEI)	N of reviews		Occupancy; RevPAR	Hotel digital marketing plan; hotel type	Linear regression	De Pelsmacker, van Tilburg, & Holthof (2018)
17	Average valence-based elasticity	Average volume-based elasticity	-	Price or average room rate	year of study; geographic setting; panel data structure; data frequency	Meta-analysis	Yang et al. (2018)
18	Aspect and overall ratings	-	-	RevPAR	-	Linear regression	Nieto-Garcia et al. (2019)
19	Online rating	-	-	Revenue	Hotel class; rooms; employees; operating expenses	DEA	Mariani & Visani (2019)
20	-	N of positive / negative reviews	-	RevPAR	Brand (ACSI)	Log-linear regression	Gao et al. (2020)
21	Cumulative Rating	Cumulative N of reviews	Degree of helpfulness	RevPAR	Seasonality	Hierarchical panel regression	Mariani & Borghi (2020)
22	Sentiment scores and overall ratings	-	-	Occupancy	-	Long Short-Term Memory Networks	Chang et el. (2021)
23	Overall rating	-	-	Sentiment scores	eWom length, readability, hotel attributes ratings	Linear regression	Aakash and Aggarwal (2022)

Table 2. Descriptive statistics on sentiment scores

Overall							Per hotel	
Mean	Median	Max	Min	SD	Skewness	Kurtosis	Avg. N of reviews	Avg. sentiment score
71.5	93	100	0	36.3	-0.985	2.404	111	70

Table 3. Summary and Description of Variables

Variables	Description	Operationalization
OR	Occupancy Rate	Occupied rooms/available rooms (in %)
ADR	Average daily room rate	Daily revenue / number of occupied rooms (in RMB yuan)
RevPAR	Revenue per available room	Quantitative variable (in RMB yuan)
Sent	Daily sentiment score for a specific hotel	Scale (0-100)
Channel 1	Smartphone app of the distribution company	Nominal-dichotomous 0=no bookings 1=bookings received
Channel 2	The company's WeChat mini-program	Same as above
Channel 3	The company's mobile website*	Same as above
Weekend	Whether it was a weekend day	1=weekend day 0=weekday
Days in operation	Days in operation of the hotel since opening	Quantitative variable (number of days)
Month	The month in which a booking was made: **Jan***, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec	Nominal-dichotomous 0=no bookings 1=bookings received
Baseline variables		

Table 4. Variance inflation factors (VIF) of the independent variables

Variable	VIF
Sent	1.0166
ADR	1.0136
Channel 1	2.1670
Channel 2	2.1755
Weekend	1.0021
Days in operation	1.0040

Table 5. Effect of daily sentiment on OR, ADR and RevPAR

	Equation 1 ADR Sent(-1)	**Equation 2 ADR Sent(-7)**	**Equation 3 ADR Sent(-14)**	**Equation 4 OR Sent(-1)**	**Equation 5 OR Sent(-7)**	**Equation 6 OR Sent(-14)**	**Equation 7 RevPAR Sent(-1)**	**Equation 8 RevPAR Sent(-7)**	**Equation 9 RevPAR Sent(-14)**
Sent	0.1822a (0.0546)	0.1930a (0.0541)	0.2416a (0.0569)	-0.0597b (0.0263)	-0.0519b (0.0265)	-0.0466c (0.0266)	-0.1829b (0.0780)	-0.1874b (0.0798)	-0.1156b (0.0473)
$Sent^2$	-0.0023a (0.0005)	-0.0023a (0.0005)	-0.0028a (0.0005)	0.0009a (0.0002)	0.0007a (0.0002)	0.0007a (0.0002)	0.0021a (0.0007)	0.0021a (0.0007)	0.0015a (0.0004)
ADR	-	-	-	-0.0363a (0.0052)	-0.0355a (0.0052)	-0.0368a (0.0052)	0.1018a (0.0201)	0.1004a (0.0202)	0.1293a (0.0155)
Channel1	0.8795 (1.2220)	1.0456 (1.2222)	1.1382 (1.2202)	-21.6391a (0.4991)	-21.7416a (0.5027)	-21.6200a (0.5012)	-38.1169a (1.4569)	-37.8831a (1.4557)	-36.4122a (0.9337)
Channel2	-1.7898 (1.7423)	-1.5619 (1.7660)	-1.3273 (1.7844)	-35.6500a (0.4882)	-35.2666a (0.4916)	-35.5172a (0.4899)	-70.3613a (1.6216)	-70.1186a (1.6382)	-66.5191a (1.0666)
Weekend	3.3987a (0.9072)	3.4957a (0.9036)	3.4024a (0.9055)	1.2059a (0.4310)	1.1682a (0.4294)	1.1972a (0.4300)	2.5190b (1.2007)	2.4348b (1.1965)	2.4149a (0.7795)
Days in operation	0.0021 (0.0019)	0.0016 (0.0018)	0.0021 (0.0019)	-0.0020b (0.0010)	-0.0015 (0.0010)	-0.0018c (0.0010)	-0.0012 (0.0027)	-0.0015 (0.0027)	-0.0025 (0.0017)
Constant	98.45a (1.7037)	89.28a (2.4147)	87.84a (2.8769)	38.76a (0.9670)	43.77a (3.9355)	45.55a (6.4570)	27.37a (3.0723)	32.22a (6.9476)	24.7126a (4.2371)
Hotel fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Copula correction *Sent*	0.8298c (0.4273)	0.8238b (0.4188)	0.8748b (0.4242)	-	-	-	1.1582b (0.5817)	1.0575c (0.5756)	-
R-squared	0.743	0.744	0.744	0.342	0.354	0.347	0.322	0.323	0.331
Adjusted R-squared	0.741	0.742	0.743	0.340	0.352	0.346	0.318	0.319	0.329
F-statistic	444.1a	448.1a	446.4a	173.0a	182.2a	177.4a	72.1a	72.5a	164.8a
Observations	10049	10076	10010	21677	21684	21677	10049	10076	21684

Note: a=prob<0.01; b=prob<0.05; c=prob<0.1

Figures

Figure 1. A screenshot from the Chinese review and booking app Meituan

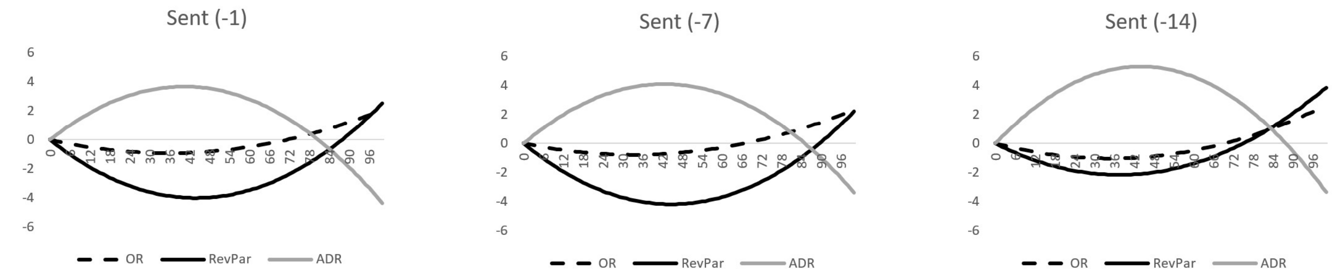

Figure 2. Curvilinear effect of sentiment on ADR, OR and RevPAR