The Impact of Online Reviews on Hotel Ratings through the Lens of Elaboration Likelihood Model: A Text Mining Approach

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Received August 2, 2023; revised September 9, 2023; accepted October 3, 2023; published October 31, 2023

Abstract

The hotel industry is an example of experiential services. As consumers cannot fully evaluate the online review content and quality of their services before booking, they must rely on several online reviews to reduce their perceived risks. However, individuals face information overload owing to the explosion of online reviews. Therefore, consumer cognitive fluency is an individual's subjective experience of the difficulty in processing information. Information complexity influences the receiver's attitude, behavior, and purchase decisions. Individuals who cannot process complex information rely on the peripheral route, whereas those who can process more information prefer the central route. This study further discusses the influence of the complexity of review information on hotel ratings using online attraction review data retrieved from TripAdvisor.com. This study conducts a two-level empirical analysis to explore the factors that affect review value. First, in the Peripheral Route model, we introduce a negative binomial regression model to examine the impact of intuitive and straightforward information on hotel ratings. In the Central Route model, we use a Tobit regression model with expert reviews as moderator variables to analyze the impact of complex information on hotel ratings. According to the analysis, five-star and budget hotels have different effects on hotel ratings. These findings have immediate implications for hotel managers in terms of better identifying potentially valuable reviews.

Keywords: Online consumer review, Online hotel ratings, TripAdvisor, Elaboration Likelihood Model, Sentiment mining

We express our thanks to Academic Editor and Reviewers.

http://doi.org/10.3837/tiis.2023.10.001 **ISSN : 1976-7277**

1. Introduction

Online consumer reviews (OCRs) are a type of user-generated content that provides essential information for experiential products [1]. The OCRs have become an important source of information for consumers and businesses [2], successfully transferring marketing communication rights from marketers to consumers, and involving them in the information creation and selection process [3]. According to previous studies, 90 percent of customers who search for and experience products sold online base their purchasing decisions on OCRs [4]. The hotel service industry is an example of experiential service [5]. As consumers cannot accurately assess the content and quality of experiential services before booking, it is necessary to explore a large amount of information during the decision-making process to reduce perceived risk [6]. When OCR is digital, consumers are influenced by online reviews to make informed purchases of experiential products. Consumers leave open-text comments, photos, videos, and other details sharing their experiences and providing a brief evaluation of a product or service. The Internet's massive, anonymous, and ephemeral nature has led to new methods for capturing, analyzing, interpreting, and managing the impact of one consumer on another. Hotels can promote their products and services by incentivizing customers to write OCRs [5].

The most critical factor in attracting customers is review content because information quality is crucial for reducing uncertainty [7]. Although online reviews provide consumers with a comprehensive understanding of a hotel, consumers would be unable to read all reviews before making decisions because each hotel receives numerous online reviews, and these are overloaded with information. Consequently, TripAdvisor has created a feature called "Was this review helpful?" To assist customers in quickly identifying the most helpful reviews among numerous reviews [8]. This function is important for the customers as well as hotel managers because reviews serve as a tool for consumers in decision-making and for managers to improve their service quality and affect overall hotel ratings. These reviews have a significant impact and are considered the most valuable [9]. Therefore, before influencing a potential customer's decision, managers should identify and fix the issues reported in reviews that are rated as most helpful.

In addition to the content of the reviews, consumer reviews with different power distances influence hotel ratings [10]. Globalization has made it easier for people to travel worldwide and increased the number of international guests in hotels. The hotel industry is highly globalized, with clients from various cultural backgrounds. Therefore, cultural factors influence consumers’ choice of hotels and the hotel industry. Globalization has enhanced the growth of online hotel industry review data. This data enhances the provision of service evaluation by consumers from various cultural backgrounds. Existing research has found cultural differences in the generation and utilization of online reviews [11]. According to previous analyses of online review data, consumers’ individualism affects their propensity to conform to prior emotions [12]. Emphasizes the importance of additional cross-cultural comparisons of online review generation and dissemination behavior [13]. Consequently, online hotel industry reviews provide ideal and rich data on customers from various backgrounds, allowing us to discuss how customers' cultural values influence their hotel ratings.

Additionally, individuals tend to seek advice from experts when making purchasing decisions, because they perceive the information provided by experts to be more accurate. In previous studies, reviews by experts were perceived as more helpful than others, and the credibility of information was based on the expertise of the reviewers [14]. Online reviews are customers' honest feedback on hotel facilities and services because online reviews are a kind of unstructured text, and data analysis is difficult. A previous study applied sentiment analysis to unstructured natural language processing of online reviews [15]. Primary text sentiment analysis examines text sentiment polarity and intensity [16]. Sentiment polarity is divided into two poles: Positive appreciation and affirmation; and negative criticism and negation [17]. Mining the emotional tendencies of customers' online reviews plays a significant role in the context of big data and innovative business models for marketing strategies [18]. A customer satisfaction database was built by converting the natural language descriptions of customers into structured data. The opinions and emotional attitudes expressed by customers in the evaluation of a specific aspect of the hotel's software and hardware can be interpreted as the customer's "vote" on the hotel's satisfaction level in the review and can be transformed into the customer's opinion of the hotel. In this context, this study further discusses the impact of the complexity of evaluation information on hotel ratings using Elaboration Likelihood Model(ELM) . The cognitive fluency theory states that an individual's subjective experience of difficulty in processing information and the recipient's attitude or behavior is influenced by the complexity of that information. According to this theory, when people cannot process complex information, they resort to peripheral routes. However, individuals who can process more information prefer to use a central route. Therefore, we distinguish between two sets of OCR features: Peripheral and central routes.

Furthermore, although previous research has demonstrated that OCR content influences consumer decision-making, we categorize OCR characteristics as follows: Peripheral Route: 1.Platform (APP) information（including helpful votes, number of comments, comment length and city ranking of hotels）. 2.hotel characteristic information (including room types，price and country). And Cure Route: customer review information (including date of writing, date of stay and customer comments) (see **Fig. 1** and **Table 1**). Simultaneously, we differentiate between receivers (i.e., professional reviewers and novices) to determine whether information processing ability in a complex information environment affects hotel ratings for five-star and budget hotels. The data is obtained by applying Python programming to crawl the page information, and the classification of the data is shown in Figure 1. And the further processing of customer reviews, that is, the conversion of customer reviews from text to vector, the resulting vector data will be further evaluated satisfaction calculation, the calculation process is shown in the formula (2) of part 3.3.2 of this article.

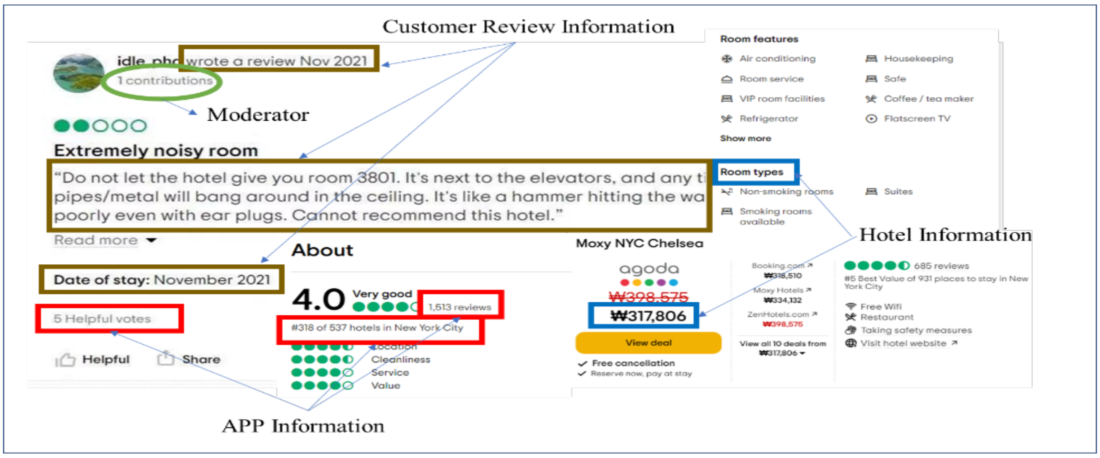

Fig. 1. Classification of information features

Table 1. Online review example

No.	Country
1	This was my first visit to the Hotel Post-Covid. And while the choice was made based on past experience, this visit was a bit of a disappointment. The rooms were spacious, well maintained and clean, but the restaurant was a disappointment. Whether for breakfast or dinner, the choices in the buffet didn't cater for International Visitors the way it did in the past. The check-in took a lot of time, and unlike previously, the staff at the check-in didn't speak English, and there was a translator assisting all the staff available at check-in.This does not negate that the staff were welcoming and trying their best to help (Hala wrote a review Apr 2023;18 contributions13 helpful votes)
2	Extremely thoughtful House-keeping staff and helpful Front-desk staff. They are attentive and thoughtful and trying their best to make their guests have a most comfortable and cozy stay in their hotel. (Prajna8688 wrote a review May 2023;Hong Kong, China1 contribution)
3	Superb if you're staying for Canton Fair - just a short walk away. Very comfortable, 5-star accommodation. Hospitable staff. Near a tram station , if you're interested in exploring other parts of Guangzhou. Didnt choose the breakfast option as this was an expensive add-on - would recommend making this a little more affordable. (DesiGary wrote a review Jun 2023;London, United Kingdom74 contributions102 helpful votes)
4	A few weeks ago, I was at Pazhou metro station and didn't know how to get to the Shangri-La Hotel. But at this point, I enquired about a passing girl who graciously led me to the hotel and showed me the shortcut after knowing that I was in a hurry for a meeting. During the conversation, I learnt that she was Hillary from the service centre, a very enthusiastic and communist-minded intern.Thanks to her for her help. (Alexander L wrote a review Aug 2023;1 contribution)

Our empirical investigation yields three intriguing results. First, the five-star and budget hotels differ in obtaining more reviews that help vote for hotel ratings. Second, reviewers from high power distance cities or regions positively and significantly impact hotel ratings. Third, expert evaluations have a restrictive moderating effect on consumers' online evaluation satisfaction and hotel ratings.

The remainder of this paper is organized as follows. Section 2 discusses the related literature and hypothesis development. Section 3 describes the econometric model specifications and variables. Section 4 presents the empirical results. Section 5 discusses the primary findings, implications, limitations, and directions for future research.

2. Literature Review and Hypothesis Development

Given the significance of online reviews, this study investigates the effect of peripheral and central routes in ELM on hotel ratings for various types of hotels (five-star hotels and budget hotels). The first type of cue is peripheral route, which is a simple cue in a message that can influence the recipient's attitude. These routes temporarily affect the recipient's attitude, and may not indicate the recipient's final judgment of the message. The central route is the second type of cue, which refers to the more complex cues of the message that require more cognitive effort for the recipient to evaluate. Individuals begin processing information via the peripheral route, and if these routes do not affect their attitudes, they stop analyzing additional information [19]. A study on Yelp.com hotel reviews revealed that the peripheral route is associated with reviewers and platform recommendations, whereas the central route is associated with reviews. Consequently, the peripheral route is defined as a simple sign that influences perception during the early stages. Central cues are more complex and influence information processing in the later stages. For example, if the platform's recommendation information is on the periphery, the hotel's characteristics are on the central route, and customer reviews are on the central route.

In terms of simple information processing, we first investigate how helpful votes affect online hotel ratings in the platform's recommendation information. Several studies were conducted to determine the value of reviews by analyzing their content using natural language processing. The effect of review length was investigated using machine learning approaches, such as support vector machines and found that review length significantly influences perceived helpfulness [20, 21]. Second, regarding a hotel's characteristic information, research power distance influences online hotel ratings. Numerous studies have confirmed that external factors such as society influence the online ratings [22] Previous research has found that customers' power distance has a significant impact on their service expectations, perceived service quality, and relationship quality [23, 24].

In terms of complex information processing, consumer satisfaction with the hotel experience is reflected in the evaluation valence (positive/negative). Positive reviews boost sales, whereas negative reviews are more likely to attract votes and are regarded as useful [25]. Negative reviews are less ambiguous than positive reviews in terms of decision-making [26]. Negative reviews are more credible than positive ones for consumers of experiential products who rely on others' opinions and advice, particularly when reviewers disclose their identities (which most reviewers do) [27]. On TripAdvisor, destination experts receive more assistance from other community voting members than from general members, demonstrating that the review generator status is significantly positively correlated with review usefulness [28]. The users on review platforms who are designated as experts by the platform, such as TripAdvisor's "contributions" reviewers are considered as professional online reviewers in this study. To define review experts, professional online reviewers must have a large number of above-average-quality reviews. Readers are more likely to perceive favorable reviews from reviewers.

A hotel rating is a consumer's overall assessment of a product or service [29]. It typically reflects consumers' satisfaction with products or services on a scale of one to five stars, with one star indicating extreme dissatisfaction and "five stars" indicating extreme satisfaction [28, 30]. Hotel ratings enable potential customers to quickly assess reviewers' attitudes and the quality of products or services [8]. Moreover, hotel ratings enable potential customers to quickly assess reviewers' attitudes and the quality of products or services [31], which evoke the interest of potential customers and influence their purchasing decisions.

Skewness is a measure of the asymmetry in distributions. We can determine the author's rating habits for attractions based on the skewness of the rating distribution and discover the author's rating habits for hotel ratings. In contrast to the mean, the skewness measures the relative positions of the mode and mean, making the shape of the distribution more intuitive. **Fig. 2** depicts three types of skewness. There is negative skewness on the left, indicating that authors are more likely to give higher ratings. In the middle, neutral corresponds to a nearly normal rating distribution. The one on the right represents positive skewness indicating that the authors are likely to give it a lower score. The means of all three distributions are comparable (3.18 on the left, 3 in the middle, and 2.82 on the right). According to the distribution, consumers are more willing to heed negative voices to avoid loss when searching for information online. According to prospect theory, consumers are more likely to read negative reviews to avoid loss and provide useful votes [32]. Emotions from pain and loss are stronger than happiness [33]. Consequently, consumers are more willing to hear negative voices to avoid losses when searching for information online. We hypothesize that receiving more review usefulness votes is often associated with negative news reviews, which impact

hotel ratings. Thus, we propose the following hypotheses:
Hypothesis 1a. Obtaining more helpful review votes negatively affects five-star hotels.
Hypothesis 1b. Obtaining helpful review votes negatively affects budget hotels.

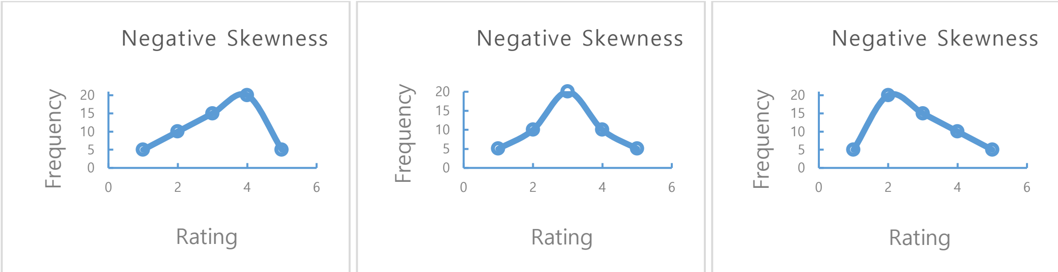

Fig. 2. Three types of skewness

Globalization has enhanced the growth of online hotel review data that provide service evaluation for consumers from various cultural backgrounds. According to the existing research, there are cultural differences in the generation and use of online reviews [11]. Based on a previous analysis of online review data, consumers' individualism influences their proclivity to adapt to prior emotions [12]. Power distance is defined as "the extent to which a society accepts the fact that power is distributed unequally in institutions and organizations" [34]. There exists differentiated power between service providers and customers in societies with greater power distance because of the philosophy of "the consumer is always right" or "the customer is king" [10]. Consumers from high-power-distance societies are likely to perceive service quality as low quality and rate service providers very poor owing to their high expectations for service [35].

Table 2. The Nations and Cities - Power Distance Point

	Country	City	Power Distance Point
1	U. S. A	New York	40
2	Japan	Tokyo	54
3	South Korea	Seoul	60
4	Singapore	Singapore	74
5	China	Shanghai	80

We selected cities in various countries and regions based on the power distance points, as presented in Table 1. Chain hotels operate in various markets. As such hotels are designed to meet the needs of varied consumers from different countries rather than the needs of customers in specific regions, they require a standardized operational strategy to survive and succeed in multiple markets. As hotel chain staff can comprehensively understand the different needs of various cultural values and methods for dealing with customer problems, this knowledge must be exchanged to meet the requirements of different customer cultures [36]. While hotels in the same chain group operate in different locations and differ in quality, country, and procedure, they use similar procedures and principles to meet certain quality standards [37]. Global online hotel industry reviews provide ideal and rich customer data from various backgrounds, allowing us to discuss how customers' cultural values influence their hotel ratings. Based on the literature, the following hypotheses are formulated:

H2a. Reviewers from high power distance regions and cities positively impact five-star hotels.
H2b. Reviewers from high power distance regions/cities positively impact budget hotels.

Consumers express their real experiences, feelings, and opinions in the form of short evaluations after consumption based on cyberspace's equality and vitality [38]. According to the uncertainty reduction theory of searchable products, consumers search for and inquire about more products or services to obtain more information [39]. A large amount of review data provides consumers with deterministic reference information for their purchasing decisions. Each online review represents genuine customer feedback on hotel amenities and services. However, this unstructured text is not conducive to scientific data analysis. We investigate the use of sentiment analysis in unstructured natural language processing of online reviews [15]. Positive online reviews of hotels can bring some benefits, whereas negative reviews can negatively impact customers' perceptions and hotel purchases [40].

Professional online reviewers have higher source credibility than newcomers [10]. Researchers have discovered discrepancies between the opinions of professional online reviewers and novices [41]. In general, when the experience is extreme, consumers are more likely to write and post reviews, and evidence suggests that novices are more polarized/dichotomous in their assessments [14]. Professional reviewers with greater expertise in generating reviews have more limitations in their extreme summative evaluations. Professional online reviewers (as opposed to novices) have less influence on overall valence metrics, influencing page rankings and consumer considerations [42]. Based on the literature, we formulated the following hypotheses:

H3a. Evaluators' professionalism negatively moderates the relationship between online evaluation satisfaction and five-star hotel ratings.
H3b. Evaluators' professionalism negatively moderates the relationship between online evaluation satisfaction and five-star hotel ratings.

3. Research methodology

3.1 Econometric Model

The research model proposed in this study is based on different routes embedded in OCR. This research model investigates the impact of peripheral and central OCR routes on consumers’ hotel ratings as the outcome variable. Each online review contains numerous cues that may affect performance, necessitating more cognitive effort on the part of the person reading it. The proposed research model divides these cues into two categories based on the ELM and assesses their impact on OCR performance. Consequently, we proposed two econometric models to examine the impacts of these two sets. H1a, H1b, H2a, and H2b are tested using negative binomial regression econometric models, whereas H3a and H3b are tested using Tobit regression econometric models.

3.1.1. Peripheral route model

Model of Peripheral Route (Model I): Hotel rating is the dependent and non-negative count variable. As Helpful Votes and Cities are count variables, this study employs a count data model. The Poisson regression model assumes that a Poisson process plots the dependent variable, and is a common count data model. However, the Poisson process requires the mean to equal variance. In this study, the mean of the Helpful Votes variable is less than the variance (mean = 1.91, standard variance = 13.63), and the mean of the Cities variable is less than the variance (mean = 2.83, standard variance = 1.32). This overdispersion necessitates the use of an extended Poisson regression model. Consequently, we present the negative binomial regression model in Equation (1), relaxing the Poisson assumption that the mean should equal the variance [43].

$$P(Y = y_i \mid x_i) = \frac{\Gamma(\theta+y_i)}{\Gamma(1+y_i)\Gamma(\theta)} r_i^{y_i}(1-r_i)^{\theta} \tag{1}$$

$$\text{where } \lambda_i = exp\,(x_i'\beta), r_i = \lambda_i/(\theta+\lambda_i)$$

In Equation(1), x_i represents the vector of the independent variable and $P(Y = y_i|X_i)$ is the probability of i^{th} hotel place y rating under the condition of x_i is the hotel rating probability , y_i can represent the probability of Platform (APP) information and hotel characteristic information, respectively, and the β vector of the parameter to be estimated. Moreover, Γ, r, and θ are the distribution parameters.

3.1.2. Central route model

Model of the central route (Models II and III): Model II represents the influence of various customer review variables on hotel ratings. Model III represents the influence of customer evaluation variables on hotel rankings under the moderating effect of experts. We consider merged data with practical research significance; that is, we collect hotel data with more online evaluations compressed to a point. Uncontrolled review satisfaction is a non-negative variable, and because it is a continuous variable, it would be more appropriate to use the type II Tobit model for the central route model, y_i represents the probability of the impact of guest satisfaction on a hotel's ranking, x_i represents the vector of customer satisfaction for the independent variable in Equation (2), β is a parameter vector of each variable of the customer testimonial information to be estimated and u_i stands for unoberviced factor.

$$y_i = \begin{cases} y_i^* & if\ y_i^* > 0 \\ 0 & if\ y_i^* < 0 \end{cases} \tag{2}$$

$$\text{where } y_i^* = x_i'\beta + u_i$$

3.2. Data Collection and Processing

Fig. 3 depicts the system design for the data collection and mining processes. We write a web crawler in Python to obtain review data for hotels on TripAdvisor.com for automatically crawling data from December 2021 to June 2015. Figure 1 depicts the system design for the data collection and mining processes. TripAdvisor.com is the most popular travel website in the world, with over 500 million travel reviews and recommendations, and over 200,000 new reviews added every day. From the website, we collected the data of 57,853 reviews from 80 hotels in five cities and excluded null or abnormal values from all 9,143 observations of data, yielding 37,023 observations of valid data.

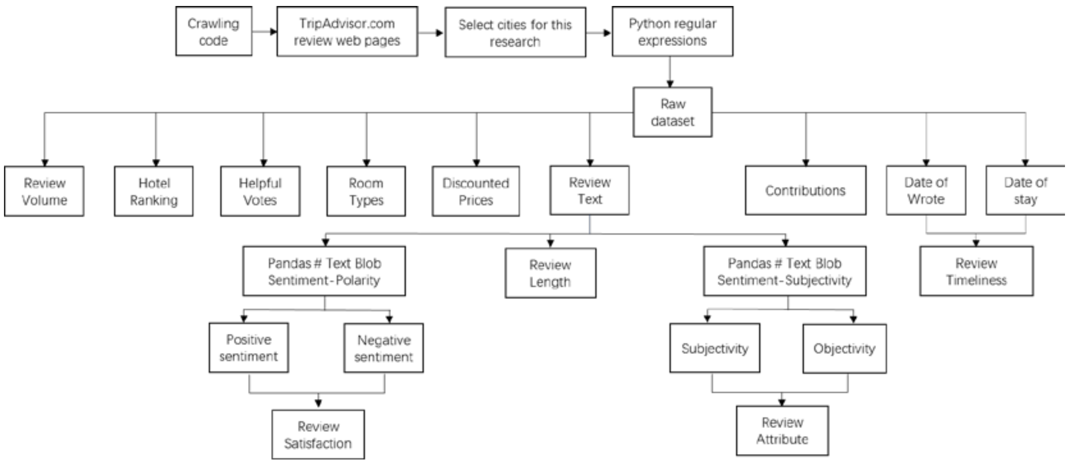

Fig. 3. System design of data collection and mining process

3.3. Variables

3.3.1. Dependent variable

Hotel ratings are the dependent variable. Based on consumer evaluations of hotel products or services, the booking platform rates partner hotels from one to five, with one being the lowest rating and five being the highest.

3.3.2. Independent variables

We considered two groups of independent variables. One set includes variables from the peripheral route model. The first is called Helpful Votes. According to previous research, reviews of usefulness vote pairs have a significant effect on hotel ratings. The second is the City. We classify numbers 1–5 as 1. USA, 2. Japan, 3. South Korea, 4. Singapore, and 5. China.

Using sentiment mining technology, natural language user evaluations are transformed into a structured user sentiment database. The customer's opinion and emotional attitude toward a specific aspect of the hotel expressed in the evaluation can be interpreted as the customer's "vote" on the level of satisfaction with this element of the hotel in the review. Count the frequency of hotel feature words in the evaluation set [44] and the emotion frequency vector of hotel feature words in (1), (i =1, 2, 3, …, n), $F(W_i +)$ represents the frequency of positive views of the feature word and $F(W_i -)$ represents the frequency of negative views of the feature word. Therefore, consumer satisfaction with hotel feature W_i is given by (3).

$$F(w_i) = \{F(w_i +),\ \ F(w_i -)\}$$
$$S(w_i) = \frac{F(w_i+)}{F(w_i+)+F(w_i-)} \quad (3)$$

3.3.3. Moderator Variables

We contend that peripheral cues relate to popularity, whereas central cues relate to OCR usefulness. Peripheral cues to reviews can be found on an online vendor’s webpage without much cognitive effort. We predict the hotel rating impact based on the platform's recommendation information and its feature information.

Table 3. Description of variables

Variable	Description
Hotel Ratings	Ratings of partner hotels by booking platforms
Review Volume	The total amount of data published by reviewers for this hotel
Review Length	The number of characters in a review
Hotel Ranking	A comprehensive ranking of hotels on the platform
Helpful Votes	Number of favorability votes by a reader (TripAdvisor = “Helpful” votes)
Room Types	Available room types displayed by the hotel
City	Selected five countries\regions with different power distance points in 2021
Discounted Prices	The hotel offers the lowest price
Review Satisfaction	Online consumer reviews reflect consumers' satisfaction with the service or product
Review Attribute	Subjective or objective review in online consumer reviews
Review Timeliness	The time interval between the hotel date of stay and writing the review
Contributions	Platform-defined reviewing expertise (TripAdvisor= “Contributor”)

The information in the OCR is the central route, which requires consumers to spend more time and cognitive effort evaluating it [45]. We investigate the impact of multiple moderating variables on hotel ratings in customer review data. Online professional reviewers are defined as those with a large number of above-average quality reviews and higher source credibility than novice reviewers [46]. Online professional reviewers are review platform users who have been designated as experts by the platform, such as the "contributions" metric, which reflects the number of users' contributions to the platform. Generally, consumers are more likely to write or post reviews when the experience is extreme. There is evidence that novices' assessments are more polarized/dichotomous [14]. Professional reviewers with greater expertise in generating reviews have more limitations in their extreme summative evaluations.

3.3.4. Control Variables

As previously stated, the review process can be divided into two steps: (1) Consumers choose to read reviews that they believe are related to popularity and (2) consumers choose to rate the usefulness of reviews. The central cue is associated with OCR content information. Consumers stop analyzing more information once they start processing information from peripheral cues if they influence their decision-making. Peripheral cues can influence attitudes and persuade individuals to seek additional information [19]. However, consumers continue to obtain central route information if they do not receive effective decision-making guidance through peripheral line information. Finally, when conducting the statistical analysis using Models II and III, the variables in Model I serve as control variables.

Table 3 describes the variables in this study’s model, and **Table 4** lists the corresponding descriptive statistics.

Table 4. Descriptive statistics of variable

Statistics	Mean	S.E.	Min	Max
Hotel Ratings	4.31	0.36	2.00	5.00
Review Volume	2868.38	2614.11	5.00	19366.00
Review Length	88.54	48.50	1.00	251.00
Hotel Ranking	7.47	17.11	1.00	553.00
Helpful Votes	1.91	13.63	0.00	1035.00
Power Distance Point	28.20	876.30	1.00	30297.00
Discounted Prices	399620.39	339485.38	31.00	1342755.00
Review Satisfaction	0.29	0.18	-0.78	1.00
Review Attribute	0.04	0.14	-0.50	0.50
Review Timeliness	0.26	0.44	0.00	1.00
Contributions	89.95	463.76	1.00	25212.00

4. Empirical Results

We employ Pearson's correlation between the independent variables (see Table 5) to test for multicollinearity. The correlation between the independent variables is not strong, ranging from -.260 to.579, and the Variance Inflation Factor (VIF) values indicate that multicollinearity is not a problem in this study. This study combines data processing methods from Test Mining with Python's Text Blob package to analyze each comment [16]. In this study, the White and DW test methods are employed in the regression analysis to further test the model, removing some of their influence on the research model.

Table 5. Variable correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1.Hotel Ratings	1											
2.Review Volume	.383**	1										
3.Review Length	-.172**	-.160**	1									
4.Hotel Ranking	-.160**	-.029**	-.045**	1								
5.Helpful Votes	-.015	-.025*	.002	.008	1							
6.Numnber of Room Types	.579**	.438**	-.163**	-.002	-.032*	1						
7. Power Distance Point	.199**	.132**	-.169**	.179**	.057**	.158**	1					
8.Discounted Prices	.309**	.234**	.065**	-.117**	-.021	.287**	-.258*	1				
9.Review Satisfaction	.194**	.079**	-.058**	.036**	.02	.132**	.058**	.075**	1			
10.Review Attribute	.105**	-.183*	.048**	-.009	.008	-.041**	-.260**	.144**	.533**	1		
11.Review Timeliness	.045**	.083**	-.191**	.024**	-.013	.081**	.085**	-.124**	.001	-.043**	1	
12.Contributions	.002	-.020**	.056**	.009	.100**	.039**	.007	.048**	.002	-.007	-.004	1

For research Model I, we use a negative binomial regression model, and the results are presented in **Table 6.** The results rejected the hypothesis that the dispersion parameter is equal to zero because the likelihood-ratio χ^2 is 5518.02 with a p-value 0.1, and 8733.05 and with p-value 0.1 between five-star hotels and budget hotels. According to this result, the dependent variable distribution is more likely to be a negative binomial distribution than a Poisson distribution. Thus, our model selection is supported.

Hypothesis 1a: Increasing the number of helpful review votes negatively impacts five-star hotels. This is because *Helpful Votes* are negative and significant (b = -.0634, p-value < 0.5), this hypothesis is supported. The negative coefficient of *Helpful Votes* for five-star hotels indicates that when consumers are more willing to heed negative voices and avoid losses when searching for information online, the results follow the prospect theory and reviews written by pessimists receive more useful votes. A hotel with a higher overall rating receives more votes for usefulness and less, supporting H1a. However, H1b (getting more helpful reviews negatively impacts budget hotels) is not supported (b =.0015, p-value > 0.1). **Table 6** indicates that Helpful Votes positively impact the hotel rating of economy hotels; that is, when optimists have more usefulness votes, the hotel rating is higher. However, this effect is only directional and has no statistical significance. Interestingly, the weight of the Discounted Prices variable in the results is very large (coef. = -0.2681), nearly 180 times that of *Helpful Votes*, indicating that discounted prices in economy hotels are a larger factor driving hotel ratings.

Table 6 presents that the *Power Distance* with rating coefficient is significantly positive (p-value 0.001) for both five-star and budget hotels. Thus, normalizing operating values for a variety of cultures can allow hotels to moderate customers' ratings of cultural factors (e.g., power distance) toward them, with reviewers with higher power distances leaving higher ratings for hotels, and hotels with established internationally standardized operations to respond to the preferences and values of customers of different cultures. Thus, H2a and H2b are supported. **Table 7** showed that results supported H3a and H3b.

Table 6. Effects of the peripheral route on hotel ratings

	Five-Stars Hotel	Budget Hotel
Review Volume	-0.0147***	-0.0763***
Review Length	-0.0016***	-0.0016
Hotel Ranking	0.0050***	-0.0211***
Helpful Votes	-0.0634**	0.0015
Number of Room Types	-0.0152***	-0.0152***
Power Distance	0.0509***	0.0283***
Discounted Prices	-0.0226***	-0.2681**
Log Likelihood	-5371.6851	-1981.3351
LR Chi^2	4617.52	1071.19
Pseudo R^2	0.0558	0.0542
Number of Obs.	24581	21743

*p < 0.1, ** p< 0.05, *** p < 0.001

Table 7. Effects of cure route on ratings

	Five-Stars Hotels	Budget Hotels	Five-Stars Hotels	Budget Hotels
Review Satisfaction	0.2134***	0.1559**	0.0741***	0.2732***
	(0.0145)	(0.0193)	(0.0143)	(0.0308)
Review Attribute	0.1187***	-0.0410	0.0260***	-0.1203
	(0.0221)	(0.0280)	(0.0207)	(0.0470)
Review Timeliness	-0.0304	0.0077	0.0451	0.1333
	(0.0209)	(0.02037)	(0.0046)	(0.0109)
Contributions	-0.0991***	0.0690***	-0.1183***	0.0337***
	(0.00401)	(0.0087)	(0.0036)	(0.0067)

Intercepr-1			-0.0642***	-0.0960**
			(0.0117)	(0.0232)
Intercepr-2			0.0615***	0.0713***
			(0.0170)	(0.0346)
Intercepr-3			-0.0230***	-0.0829***
			(0.0046)	(0.0078)
Review Volume	YES	YES	YES	YES
Review Length	YES	YES	YES	YES
Hotel Ranking	YES	YES	YES	YES
Helpful Votes	YES	YES	YES	YES
Room Types	YES	YES	YES	YES
City	YES	YES	YES	YES
Discounted Prices	YES	YES	YES	YES
Log Likelihood	-3812.4312	-2170.6470	-3812.4864	-2169.7492
LR Chi^2	470.88	81.11	470.7700	82.91
Pseudo R^2	0.0582	0.0483	0.0584	0.0487
Number of Obs.	23,661	19,539	23,661	19,539

$^*p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.001$

5. Discussion, Implications, Limitations and Further Research

5.1 General Discussion and Implications

This study investigated the performance of OCR and examined the impact of central and peripheral routes on hotel ratings and the impact of useful voting and power distance on hotel ratings in the peripheral route. This study demonstrated this in two dimensions of peripheral routes: The platform's recommendation information and the hotel's characteristic information. First, when individuals search for information, they focus on the peripheral route and their response to the environment is determined by emotion and recognition. Based on the emotional dimension, budget hotel customers are likely to believe that the hotel they select is more suitable and cost-effective. According to the cognitive dimension, consumers of five-star hotels are more likely to anticipate the theory and pay more attention to unfavorable information. Participation in helpful votes embodies online consumers' cognition of and emotions toward websites. Second, notably, the hotel's international standard operation, which is open to various cultural values, can enable the hotel to reduce customers' cultural factors (e.g., power distance) in their ratings, thereby avoiding cultural differences among consumers in countries or regions with high power distance. Simultaneously, this study investigated the impact of customer satisfaction as an OCR performance indicator on hotel ratings. When professional reviewers act as moderators in the central route, it is important to note that greater expertise of professional reviewers in generating reviews leads to greater constraints on extreme summative evaluations.

This study makes three major theoretical contributions and discusses the practical implications for academia and practice. First, the impact of the complexity of online review information on hotel ratings has implications for future hotel management research. We investigated the OCR performance in two stages using ELM from a theoretical standpoint. In the first stage, consumers decide whether to read reviews influenced by a side trip. The second stage of consumer decision-making concerns whether the central route influences reviews. We integrate the platform's recommendation information of the peripheral path of simple information, the characteristic information of the hotel itself, and the complex information of the customers of the central path of comment information owing to the high value of online reviews. While most studies on the impact of hotel ratings have concentrated on aspects such as hotel pricing or service quality [46, 47]. Unlike previous studies that only considered one or two influencing factors to determine the impact on the hotel industry, this study considered the differences in the cognitive fluency of different individuals when it comes to information. Cognitive fluency makes it difficult for individuals to process information. a degree of subjective experience [48]. Consumers use OCR to find the information they require or to compare different options. When people seek information, they prioritize the peripheral route during the reading phase, whereas the central route is useful for surrogate comparisons. This study described OCR as a potentially cost-effective method for marketing hotels and discusses some of the emerging technological and ethical issues that marketers must deal with as they seek to capitalize on these emerging technologies. Second, this study helps improve the prediction and regression models for online hotel reviews. To the best of our knowledge, this review aims to discuss the dependent variables in the context of different cognitive paths or to conduct research on two types of representative hotels (five-star and budget hotels).

This study explored the value of reviewers' historical helpful votes for hotel ratings, whereas previous research has focused only on aggregated reviewer statistics [49], such as the number of comments received and the number of helpful votes cast. Simultaneously, we investigated the impact of customers from cities with different power distances on hotel ratings, whereas previous research focused merely on cultural differences [50] to avoid cultural differences and disregard the standardization of hotel internationalization. Furthermore, we investigated the relationship between customer satisfaction and hotel ratings, whereas previous studies have only examined the impact of the valence of online consumer reviews on hotels [51]. The primary results indicate a moderating relationship between expert satisfaction and hotel ratings. The empirical findings indicate that different cognitive pathways influence hotel ratings. This finding has implications for research related to prediction as well as causality/correlation relationship research. Investigate the online hotel review prediction problem to improve prediction accuracy.

Finally, from a methodological perspective, we employed a negative binomial regression model to investigate the factors influencing peripheral routes. Most previous studies used linear regression models with ordinary least squares (OLS) estimates or logistic models. However, while a count model would more appropriately avoid biased estimates of the number of helpful votes, the negative binomial regression model is better suited for the data in this study. Simultaneously, we employed the Tobit model to investigate the factors influencing the central route. The data were highly concentrated and merged, and at one point, the observed data were compressed into a non-negative variable. This necessitated the use of the negative binomial regression model and Tobit model in this study. The research on hotel management methodologies paves the way for new research directions, which is crucial for hotel management.

5.2 Limitations and Further Research

This study has some limitations that require additional research. First, we only used hotel OCR in New York, Tokyo, Seoul, Singapore, and Shanghai. Although these cities are ideal for our research, the stability of the model must be confirmed using a broader range of hotel data. Secondly, in the process of crawling pages using python, incomplete data crawling, data loss, etc., so there will be default values in the process of measuring statistics, although there is no impact on the results. However, programming techniques should be refined in subsequent research to obtain more stable and accurate databases. Finally, in addition to considering the three types of information variables of Platform (APP) information， hotel characteristic information and customer review information, we can further consider the weather on the day of check-in and the weather on the day of departure in future ，and measure the impact of bad weather changes on customer review satisfaction. In addition to, the influence of word attributes (such as rational meaning, color meaning, stylistic color, etc.) in customer reviews on the helpful of consumers' reviews can be further explored. Alternatively, measuring how long consumers are separated from their review dates can have a positive impact on readers. The above ideas have not been realized due to the limited space of the article, and it is hoped that this part of the work will be carried out when the opportunity and ability are available.

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