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Moderating Effects of Rating on Text and Helpfulness in Online Hotel Reviews: An Analytical Approach

Abstract

An online review is composed of various information components (e.g. reviewer profile, review rating, and text), which may have impacts on its user simultaneously. However, while there is a growing interest in understanding the information value of online reviews, the potential interaction effects between different review components have rarely been examined. This study aims to explore the interaction effects on individual perception between review rating and review text in the online hotel review context. We conducted an analytical exercise using actual hotel reviews collected from three major review websites to understand the interaction effects that took place in real, potentially complex settings. Findings showed that review rating and review text interact with each other, and individual perception of hotel reviews varies with the interactions. Finally, we discuss the implications for the holistic perception of online reviews and interactive roles of review components as well as limitations and future research directions.

Keywords: online hotel reviews; eWOM; interaction effects; review rating; review text; social media analytics.

1. Introduction

Imagine you are searching for a hotel to stay for an upcoming trip. You log into TripAdvisor, Yelp, or Expedia to check online reviews. Although there are a huge number of reviews, it is impossible to go through all of them. Thus, you filter out less relevant reviews by using review rating. If you want to know which hotel attributes are positively evaluated, reviews with high ratings will be selected and vice versa. While reading the text of selected reviews, you already have impressions about the hotels, which could influence your perception of their information value.

An online review is a bundle of information components, such as reviewer profile, review rating, review text, review helpfulness vote, and so on (De Pelsmacker, Dens, & Kolomiiets, 2018; Liu & Park, 2015; Xiang et al., 2017). The above scenario suggests that travelers process online reviews by considering the different components together, indicating that the informational value of an online review is hardly determined by a single component (Fong, Lei, & Law, 2017). While there has been significant growth in research with the goal to understand the nature and impacts of online reviews as electronic word-of-mouth (eWOM) (Hong et al., 2017), most existing studies have examined the effects of review components in isolation, leaving much to be desired in understanding the holistic impact of this type of eWOM on consumers (Hu, 2019; Pentina, Bailey, & Zhang, 2018).

As such, this research aims to explore how the interaction effects of different review components influence an individual's perception in the online hotel review context. Specifically, the moderating effects of review rating on the relationship between review text (in terms of its semantic and linguistic features) and review helpfulness are examined. To test these effects, we conducted a series of analyses with a large dataset of online hotel reviews collected from three major review websites. This research contributes to the literature on eWOM in hospitality and tourism by providing insights into the integral structure of user-generated content (UGC) using an analytical approach.

2. Research Background

Online reviews have become essential information sources that support consumers' decision-making (Book et al., 2018). They are especially significant in the hospitality and tourism field because of the experiential nature of travel (Akhtar et al., 2019; Assaker, 2019). As such, a growing body of hospitality and tourism literature has been published to understand the perceptual aspects of online reviews to ascertain how travelers process reviews. This line of research has adopted review helpfulness as a primary outcome variable and examined the impacts of various review components, such as reviewer profile (Fang et al., 2016), review rating (Liu & Park, 2015), and review text (Park & Nicolau, 2015; Xiang et al., 2017; Xiang et al., 2015), on review helpfulness. In general, this literature has documented the perceived value of online reviews in terms of each component's individual effect. The way in which different review components interact with each other and generate a holistic effect on review helpfulness is not well understood in the context of hospitality and tourism (Hu, 2019; Pentina et al., 2018). However, considering that individuals process multiple information components simultaneously, it is important to understand the possible interactions between different review components and their holistic impacts on readers' perception (Kim, Maslowska, & Malthouse, 2018).

Several theoretical frameworks provide the foundations to study an individual's holistic perception of information such as the Elastic Capacity Model (ECM) (Kahneman, 1973) and Heuristic-Systematic Model (HSM) (Chaiken, 1980). As models of information processing strategies, HSM and ECM assume 1) that there are two distinctive processing routes, i.e., a central (systematic) route involving the careful processing of the main content of information and a peripheral (heuristic) route associated with simple decision-making rules about the auxiliary content, and 2) that these two different processing routes may occur concurrently, indicating individuals' capacities of parallel information processing (Bohner, Chaiken, & Hunyadi 1994; Lord, Lee, & Sauer, 1995). Although these models have not been directly applied to the research on the interactions between online review components, some studies have adopted their basic assumptions to address the lack of a holistic approach in the context of travelers' information processing. Schlosser (2011) identified several interaction effects between review rating and review text valence through a couple of experiments: 1) a review explaining both the pros and cons of product (i.e., two-sided review) tends to be more helpful when its rating is moderate; 2) when the rating is extremely high or low, a one-sided review is more persuasive than a two-sided review. Similarly, Zhou and Guo (2015) found that review helpfulness is likely to increase when review rating and review text valence are consistent. By comparing the individual rating (e.g., rating for a hotel room, service, or location) and individual sentence (e.g., sentence describing a hotel room, service, or location), Zhang et al. (2016) discovered that consumers maintain consistency between review rating and review text valence while evaluating products.

Although prior studies investigated travelers' information processing behavior by supposing that travelers consider different review components simultaneously, they have primarily focused on the "likelihood" of the behavior. As existing research based on HSM and ECM has been conducted through surveys or experiments, there are several inherent limitations in reflecting the real, potentially complex online contexts (Watts & Zhang, 2008; Zhang et al., 2016). Online systems, especially social media platforms such as review websites, are complex systems that involve different technological affordances and variations that support socio-cultural interactions (Scott

& Orlikowski, 2012; Tufekci, 2014; Xiang et al., 2017). Given the variation and complexity of social media platforms, it is important to examine what actually happens in the real world in order to understand the behavior of social media users. As such, we propose to use social media analytics with the goal to develop an understanding of travelers' information processing behavior in relation to eWOM by examining how they actually assess online reviews in a holistic way. Social media analytics, by combining Web crawling, text analytics, and statistical techniques in association with a large amount of social media data, is considered advantageous for understanding these online circumstances (Giardullo, 2016). As demonstrated in a growing amount of literature (e.g., Fan & Gordon, 2014; Xiang et al., 2015), social media analytics has enabled researchers to "directly observe" the actual behavior of social media users (Anderson, 2008; Boyd & Crawford, 2012).

3. Research Framework and Hypotheses

This research aims to examine the interactions between review components to understand traveler's holistic perception of online hotel reviews using methods developed in social media analytics. As the major goal of this research is assessing how travelers process online reviews in the real setting, we focus on the plausible interactions between review rating and review text rather than considering all potential possibilities of interactions between any review components. Specifically, we focus on the moderating effects of review rating on the relationships between review text and review helpfulness. Practically, review rating and review text are the common components available in most review websites and, theoretically, both have been demonstrated as the important review components which represent core contents of online reviews (e.g., Chua & Banerjee, 2015). Further, review helpfulness has been extensively utilized as a measurement of the reader's perception of information value of online reviews (e.g., Xiang et al., 2015).

Review rating represents overall evaluation about the subject: higher rating usually indicates a positive evaluation and lower rating a negative one. From the analytics perspective, review text can be deconstructed into three textual features, namely sentiment (e.g., valence of text), semantic (e.g., keywords of text), and linguistic (e.g., length or readability of text) (Xiang et al., 2017). Although review text valence has a significant impact on review helpfulness (Cao, Duan, & Gan, 2011), it is found that reviewers tend to interpret the valence of text in consistence with review rating to avoid cognitive dissonance (Zhou & Guo, 2015). This indicates that these two components are usually consistent and, therefore, we consider it not meaningful to examine them together in terms of interaction effects. As such, sentiment features are excluded.

Semantic features refer to the meanings of the text, which can be represented by keywords and their associations (Xiang et al., 2017). In the case of hotel reviews, the keywords are reflective of hotel attributes (e.g. location, staff, service, and room, etc.) and semantic features can be understood as "topics" about hotel attributes mentioned in review text. In this research, hotel attributes are defined as the extent to which various topics of hotel attributes (e.g., staff service, location, dining facility) are mentioned in review text. Considering different travelers' information needs, the helpfulness of hotel reviews oftentimes reflects the extent to which hotel attributes are mentioned in review text; that is, review helpfulness has strong correlations with specific topics mentioned in review text (Xiang et al., 2017; Xu, 2018).

H1. The extent to which topics of hotel attributes are mentioned in review text (referred to as hotel attributes hereafter) has a significant effect on review helpfulness.

The moderating effect of review rating on hotel attributes can be explained by Herzberg's two-factor theory (Herzberg, Mausner, & Snyderman, 1958; Herzberg, 1968). According to this theory, individual's satisfaction and dissatisfaction are determined by two independent sets of causes, namely satisfiers and dissatisfiers (Herzberg et al., 1958). While the higher performance of satisfiers increases an individual's satisfaction, dissatisfiers only prevents individuals from being satisfied; as such, this means dissatisfiers cannot be managed to improve satisfaction (Herzberg, 1968). In the hotel context, the higher quality of satisfiers (e.g., business services, safety and security) would give guests a pleasant surprise (Qu, Ryan, & Chu, 2000), but that of dissatisfiers (e.g., cleanliness, bed comfort) allows the hotel to be perceived as fulfilling its basic conditions (Dolnicar, 2002). On the contrary, dissatisfiers' low performance gives hotel guests unacceptable experiences. For travelers who search for the hotel to stay, the extent to which satisfiers are positively evaluated matters more than how much dissatisfiers are positively evaluated, because they would like to choose the exceptional hotels rather than mediocre ones. That is, the extent to which dissatisfiers are negatively evaluated is more important than how much satisfiers are negatively evaluated because terrible hotels have to be avoided (Bodet, Anaba, & Bouchet, 2017). When satisfiers (dissatisfiers) are major topics of hotel reviews, a positive review (or a negative review) might be perceived as more helpful for travelers to choose the available option (or to avoid). As such, the helpfulness of hotel reviews, which reflect the evaluation of hotel attributes as either satisfiers or dissatisfiers, changes in relation to the negative or positive evaluation of the experience (i.e., rating).

H1a. Review rating moderates the effects of hotel attributes on review helpfulness. Some hotel attributes (dissatisfiers) increase helpfulness when they match *with negative rating, while others (satisfiers) increase helpfulness when matching with positive rating.*

Linguistic features are textual characteristics. Among many linguistic features (e.g. length, readability, relevancy, timeliness, completeness, and so on), length is often seen as one of the important features as confirmed in other studies (Hong et al., 2017). It represents the amount of information and has been found with a significant positive impact on review helpfulness (Fang et al., 2016; Mudambi & Schuff, 2010).

H2. Length has a significant positive effect on review helpfulness.

With respect to moderating effect of review rating on length, it can be explained by the individual's different expectations about positive or negative information. In the online review context, writers are likely to describe their negative experience with more details rather the positive one, so readers tend to expect more concrete information when they see negative reviews (Herr, Kardes, & Kim, 1991). The amount of information matters more when it is negative evaluation (Lee, Park, & Han, 2008). Thus, it is suggested that the influence of length on review helpfulness is increased when reviews have low rating.

H2a. Review rating moderates the effect of length on review helpfulness. The effect of length on helpfulness is increased when review rating is low.

Readability, another linguistic feature, refers to the ease of understanding review text. Similar to length, research has shown that readability has a significant positive impact on review helpfulness (e.g., Yang et al., 2017). However, many previous studies suggested that attempts to draw any inferences on the relationship between review rating and readability may not allow for particularly meaningful inferences either theoretically or practically (Schlosser, 2011; Zhang et al., 2016; Zhou & Guo, 2015). This is because the importance of review text quality (e.g., readability) in determining review helpfulness is so strong that its impact on review helpfulness is not easily affected by other review components, including review rating (Wu, van der Heijden, & Korfiatis, 2011). The specific aim of this particular research is to investigate possible interactions between review rating and text, rather than to explore other possibilities that may exist, but would, nonetheless, be less relevant. Thus, based on the evidence provided by the aforementioned literature, we decided to disregard an unlikely interaction between review rating and readability, and focus instead on what we believe to be more meaningful - i.e., the impact of readability on review helpfulness.

H3. Readability has a significant positive effect on review helpfulness.

[Figure 1 here]

4. Research Methodology

4.1. Data

Online hotel reviews written in English collected in a previous study (Xiang et al., 2017) were adopted, in part, to test the hypotheses. In late 2015, hotel reviews about properties located in Manhattan, NYC were collected from TripAdvisor, Expedia, and Yelp using Web crawlers written in Python and Java programming languages. Manhattan was selected because there are many different hotels located in that region in terms of service level (e.g., budget, mid-range, and luxury hotels) and type (e.g., business, boutique, and leisure hotels). There are several reasons for choosing the three websites: 1) they are commonly used by travelers (Penaflorida, 2018); 2) each of them represents a unique type of review website (i.e., TripAdvisor and Expedia are the largest travel review website and an online travel agency (OTA), respectively, while Yelp is the dominant website for local businesses) (Frank, 2014); and, 3) they have been widely adopted as data sources in the research within and outside the hospitality and tourism context. Hotel class (i.e., stars), name of hotel, review rating, review text, and the number of helpful votes were collected. Since hotel class was missing in many cases on Expedia and Yelp and only TripAdvisor discloses its information source (i.e., third-party partners such as Giata), we used TripAdvisor's data to assign hotel class to each property. First, the name and class of all searchable hotels in the three websites were collected with Web crawlers. Among over 500 hotel properties, about half of them were randomly selected to reduce the volume of data to the extent of conducting the required analyses in this research (i.e., hierarchical regression analysis and bootstrapping). After selecting the hotels, all the English-written reviews were collected. A total of 100,200 reviews were collected from 206 hotels. However, 548 reviews showed extreme inconsistencies between review rating and text valence (i.e., positive rating with negative text and vice versa), so they were expected to make a noise in the results and removed. In total, 99,652 reviews were used for the analyses. The majority of reviews were from TripAdvisor (63,374/63.6%), followed by Expedia (30,915/31.0%) and Yelp (5,363/5.4%).

4.2. Development of measures

In this research, review rating (a moderating variable) refers to the summarized evaluation of the overall hotel experience assigned by reviewers (i.e., hotel guests). The three websites adopt a five-point format, i.e., from 1 (terrible) to 5 (excellent), and the original value was used.

Before identifying the independent variables (i.e., hotel attributes, length, and readability), review text was pre-processed with tokenization and stop-word removal. We then used the text-mining methods discussed in Xiang et al. (2017) to calculate measures of the semantic and linguistic features of review text. In this research, semantic features (i.e., hotel attributes) are defined as the extent to which various topics of hotel attributes are mentioned in review text, which were identified through topic modeling using the Latent Dirichlet Allocation technique (Blei, Ng, & Jordan, 2003). Topic modeling extracts the important topics by analyzing a set of text and calculates probability indicating the likelihood of certain topics to appear in a specific text. As a result of topic modeling, four topic groups were extracted. Based on the meanings of topics in each group, they were labeled as "Value" (Attribute 1), "Landmarks and Attractions" (Attribute 2), "Dining and Experience" (Attribute 3), and "Core Product" (Attribute 4) (Table 1). These labels were used to represent the four groups of hotel attributes and each review was assigned four values (from 0 to 1). Each value represents the probability for the topics of specific hotel attributes to appear in the text. For example, if a specific review is assigned 0.40 for "Value", 0.20 for "Landmarks and Attractions", 0.70 for "Dining and Experience", and 0.80 for "Core Product", it means that the topics related to "Dining and Experience" and "Core Product", instead of hotels' value and nearby landmarks and attractions, were more frequently mentioned in the review text.

[Table 1 here]

The two linguistic variables, length and readability, were calculated using the text mining package in the Python programming language. Length is defined as the length of text and measured by the number of words written in review text. Readability refers to how easy the review text is to understand. To measure readability, the Flesch Reading Ease formula was used (Flesch, 1948). As one of the popular and accurate readability formulas, it is based on a ranking scale ranging from 0 (very confusing) to 100 (very easy-to-read) and calculated as below:

$$Flesch\ reading\ ease = 206.835 - 1.015\left(\frac{Words}{Sentences}\right) - 84.6\left(\frac{Syllables}{Words}\right)$$

Finally, the dependent variable, review helpfulness, is defined as the extent to which hotel reviews help travelers to choose the hotel to stay. Most review websites use a voting system that allows users to cast a vote for the reviews perceived as helpful, and the accumulated number of votes reflects the collective perception. Although the three platforms use slightly different terms for helpfulness votes (i.e., 'Thank reviewer' in TripAdvisor, 'Was this review useful?' in Yelp, 'Helpful' in Expedia), they have similar rules for the function with respect to soliciting reader's feedback on the review's information value. And, this measure of information value, conveniently called helpfulness vote, has been commonly used in research with cross-platform analyses (e.g., Hong et al., 2017; Xiang et al., 2017). However, only a small portion of reviews received helpfulness votes and most of voted reviews had only one vote. To address these issues, a machine learning procedure was developed to calculate and assign a helpfulness score for each review. This procedure simulated the helpfulness score based on a centroid-based summarization method (see details in Xiang et al., 2017). The helpfulness score is between 0 and 1 with a higher value indicating higher helpfulness. Table 2 shows the mean values of length, readability, and helpfulness score.

[Table 2 here]

4.3. Analyses

As the research goal is to examine the moderating effect of review rating on the relationships between review text and helpfulness, a hierarchical regression analysis was performed. Before the analysis, centralization was applied to all the variables to remove multicollinearity issues. In the first model, only the control variable, i.e., hotel class, was included. In the second model, along with the control variable, independent variables (i.e. hotel attribute, length, and readability) and moderating variable (i.e. review rating) were added to test the main effects. In the final model, interaction terms were added to test the moderating effects of review rating. All the regression analyses were conducted through the R statistical package. Due to the large sample size, even the small effects could appear significantly (Lin, Lucas, & Shmueli, 2013). In order to address this issue, 2,000 times bootstrapping was conducted for each model and the number of bootstrap sub-samples was 1,000.

5. Results

As shown in Table 3, most effects were significant. As for robustness check comparing the original and bootstrap results in terms of significance and direction, all the results appeared consistently except for the moderating effect of review rating on the impact of readability. While it was significant in the original results ($\beta = -0.000$, $p < 0.001$), it was not in the bootstrap ones ($\beta = -0.003$). After taking into account the robustness of bootstrap results, we decided to use the bootstrap results for interpretation. The R

Square and adjusted R Square increased from Model 1 to Model 2 and from Model 2 to Model 3, and all the improvements were shown significant. The control variable had a significant impact on review helpfulness. Impacts of all hotel attributes on review helpfulness were significant, but the direction of impact was different by each hotel attribute. Length and readability both contributed to review helpfulness. Review rating, the moderating variable, was positively significant. Finally, all interaction effects were significant except for the interaction between review rating and readability.

[Table 3 here]

In addition to regression analyses, a comparative analysis was conducted to compare two different models of different data sets. Length and readability had skewed distributions, which were expected to impact on the results. Hence, we log-transformed these variables and ran the same regression analyses. By comparing the two models with several estimators of relative quality of statistical models (e.g., adjusted R Square, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC)), we found the model of original sample was better than the models of transformed samples with the higher value of adjusted R Square and lower values of AIC and BIC (Ding, Tarokh, & Yang, 2017) (Table 4).

[Table 4 here]

Main effects of hotel attributes and moderating effect of review rating: All hotel attributes' main effects were significant. Thus, Hypothesis 1 was accepted. In the case of Attribute 3, a negative main effect was found, indicating the more mentioning about "Dining and Experience", the less helpful the review was perceived ($\beta = -0.013$, $p < 0.001$). On the contrary, Attribute 1 ($\beta = 0.037$, $p < 0.001$), Attribute 2 ($\beta = 0.055$, $p < 0.001$), and Attribute 4 ($\beta = 0.034$, $p < 0.001$) had positive main effects, meaning the more mentioning about "Value," "Landmarks and Attractions," and "Core Product", the more helpful the review was perceived. As for the moderating effect, it was significant in all hotel attribute cases; as such, Hypothesis 1a was accepted. The negative main effect of Attribute 3 was increased when review rating is high (β = -0.002, $p < 0.001$). Review helpfulness rapidly decreased when hotel reviews containing more topics about "Dining and Experience" had positive rating. The positive main effects of Attribute 1 (β = 0.005, $p < 0.001$), Attribute 2 (β = 0.008, $p < 0.001$), and Attribute 4 (β = 0.005, $p < 0.001$) were more increased when review rating was high. Review helpfulness rapidly increased when hotel reviews containing more topics about "Value," "Landmarks and Attractions," and "Core Product" had positive rating.

Main effect of length and moderating effect of review rating: As expected, the main effect of length was positively significant (β = 0.060, $p < 0.001$) and, thus, Hypothesis 2 was accepted. The moderating effect of review rating was also significant (β = -0.001, $p < 0.001$), so Hypothesis 2a was accepted. It was found that hotel reviews tend to be perceived more helpful when review text was longer and the importance of length was more increased when review rating was low.

Main effect of readability and moderating effect of review rating: The main effect of readability was negatively significant (β = -0.000, $p < 0.001$). Therefore, Hypothesis 3 was not accepted. In the case of moderating effect of review rating, it was not significant according to the bootstrapping results (β = -0.003).

Although hotel class was used as a control variable, all the interactions were explored in two different cases, budget (one-, two-, three-star class) and luxury hotels (four-, five-star class) to further examine the interactions in a post hoc fashion. Except for reviews about hotels without class information, 35,781 were grouped as budget hotel reviews and 61,105 as luxury ones. In terms of main effects, most results were consistent with the original results, but the main effect of readability was not significant in budget hotel case. The differences occurred more in the results of moderating effects. Although moderating effects in luxury hotels were generally consistent with original results, those of Attribute 1 ("Value") and Attribute 3 ("Dining and Experience") were not significant in the budget hotels. These results implied that the perception about some hotel attributes could be different depending on hotel class (Xu, 2018), consistent with previous research that traveler's perception of hotel attributes could be different depending on associated types of hotels (Chowdhary & Prakash, 2005) (Table 5).

6. Discussion

6.1. The main effects of review textual features

All the hotel attributes had significant effects on review helpfulness, positively or negatively. These results are consistent with previous research showing that the content of review is an important criterion when evaluating review helpfulness (Xiang et al., 2017). When the topics about "Dining and Experience" were mentioned more in review text, travelers tended to perceive the hotel reviews as less helpful. However, the more mentioning of the topics about "Value," "Landmarks and Attractions," and "Core Product", the more helpful the reviews were perceived. These findings can be interpreted by considering the characteristics of the destination where the reviewed hotels are located.

Our review data were about the hotels located in Manhattan, NYC, which is one of the most famous touristic destinations for popular landmarks and attractions, such as Broadway, Time Square, and Central Park (Li & Du, 2018). Travelers planning to visit Manhattan may expect to enjoy famous touristic places rather than relaxing in hotels. Xie et al. (2018) found that travelers of NYC tend to spend their time mostly in Midtown, Lower Manhattan, and Utica Avenue in Brooklyn, where many attractions are concentrated. In our results, the topics of “Dining and Experience” were related to hotels’ inner facilities and, thus, such information might not be important for potential travelers of the destination full of fascinating attractions. At the same time, this could be a reason why the information about “Landmarks and Attractions” was perceived helpful. These expectations are supported by the findings in the reports: 1) domestic and international travelers of NYC spend 83% of their travel expenditures in shopping but only 24% in restaurants; and, 2) the biggest expenses of international travelers of NYC incur in cultural facilities (29%) and retails (29%) (Center for an urban future, 2018). NYC travelers tend to have higher interests in shopping or visiting famous landmarks, art galleries, or museums, and it decreases the value of the less important information (“Dining and Experience”) but increases that of the more important one (“Landmarks and Attractions”). On the other hand, the higher importance of “Landmarks and Attractions” could be attributed to the importance of hotel’s location for a traveler’s decision-making (Yang et al., 2015). While the topics of “Landmarks and Attractions” might be used for describing the attractions themselves, they could also be used for explaining where the hotels are located. Given a variety of famous attractions in NYC, a major consideration for NYC travelers is the distance from the hotel to landmarks or attractions (Xie et al., 2018). However, even though the destination is known for many attractive places, the values (“Value”) and basic attributes (“Core Product”) of hotels were still important. These results are in accordance with the findings of previous studies examining a significant effect of hotel’s core attribute performance on traveler’s eWOM (Yen & Tang, 2015).

The two linguistic features, length and readability, were also shown to be significant. In the case of length, travelers usually consider the hotel reviews with the longer text as more helpful. These results were consistent with previous studies (e.g., Fang et al., 2016; Hlee et al., 2016; Park & Nicolau, 2015). As for readability, although its positive impact was hypothesized, readability had a negative impact on review helpfulness. This finding is similar to the previous research which showed hotel reviews with simple text were less helpful (Park & Nicolau, 2015). The higher readability score may indicate the easiness of the text, but, on the other hand, it represents the simplicity of the text. While simple text is beneficial for readers in decreasing their cognitive efforts, it might be perceived as a lack of sophistication (Smith, 2012). Additionally, the correlation between length and readability in our data set was examined as significantly negative (r = -0.010, $p < 0.01$), indicating that more readable text tends to contain less information.

6.2. The moderating effect of review rating

Review helpfulness of information about "Dining and Experience" rapidly decreased when review rating was high. This finding is in line with the results of previous studies that hotel's food and restaurant are examined as dissatisfiers, and that positive evaluation about the attribute is not helpful for traveler's decision-making (Albayrak & Caber, 2015; Robinot & Giannelloni, 2010). Other hotel attributes of positive main effects showed positive interactions with review rating. Review helpfulness of information about "Value," "Landmarks and Attractions," and "Core Product" increased as review rating increased, indicating that the three hotel attributes are perceived as satisfiers by hotel guests. Interestingly, "Core Product" has been examined as a dissatisfier in most previous studies, and "Value" and "Landmarks and Attractions" have been rarely identified as attributes of hotel products (Albayrak & Caber, 2015; Bodet et al., 2017; Robinot & Giannelloni, 2010; Slevitch et al., 2013).

The positive impact of length on review helpfulness was moderated by review rating as hypothesized: Review helpfulness of hotel reviews of longer text increased more rapidly when their rating is low. These findings are aligned with the results of previous studies: Online review readers tend to expect more rich information if the reviews have negative rating (Herr et al., 1991; Lee et al., 2008). Finally, the interaction between readability and review rating was not significant as expected (Schlosser, 2011; Zhang et al., 2016; Zhou & Guo, 2015).

7. Conclusion

The current study aims to examine interaction effects between review rating and text on helpfulness in the online hotel review context. To achieve this goal, the relationships between semantic and linguistic features of review text and helpfulness are explored and the moderating roles of review rating on the relationships are investigated. The results suggest that all the textual features have significant impacts on review helpfulness and that most of these effects are moderated by review rating, except the interaction between review rating and readability.

7.1. Theoretical implications

First, this study fills the existing research gap by investigating interactions in online reviews. Although a number of studies have attempted to explain the impacts of online reviews, the individual's holistic processing of online reviews has not been well understood (Fang et al., 2016; Liu & Park, 2015; Xiang et al., 2015). The present study demonstrates that different review components interact with each other and individual's perception could be affected by these interactions. The findings suggest that review components should not be studied in isolation in order to further understand how individuals actually process online reviews (Ma et al., 2018). Additionally, even within review text, different words/phrases associated with the product can interact with other information components (e.g., review rating) and generate different impacts on readers. The current study can serve as the starting point to develop our understanding about holistic perception of online reviews in that it suggests the need to investigate other interactions in online reviews. Possibly, such interactive roles of review components could be answers to why review components' direct effects on review helpfulness have been found inconsistent across different studies. For example, while some studies found a positive impact of review rating (Liu & Park, 2015; Wu, 2017), others find negative impacts (e.g., Chua & Banerjee, 2016). This study suggests that, with elaborated findings of review components' roles, nuanced explanations about integral structures of review components can be provided. As such, this research improves the conceptual foundations for understanding perception and structure of eWOM and UGC as bundles of information components in the hospitality and tourism field.

Second, our study reveals the actual patterns in users' online behavior (i.e., how the evaluation of the hotel experience is inherently connected to and has an impact on the relationships between review content and its perceived information value) by implementing social media analytics to investigate traveler's information processing with the so-called big data. Unlike survey and experiment data collected from the comparatively smaller number of travelers, online review data are aggregated opinions of a much greater number of travelers and they are written voluntarily by travelers with their actual evaluations (Ramanathan & Ramanathan, 2011). A large amount of social media data, such as online reviews have been regarded as alternative sources compared to survey and experiment data to show the actual behavior of social media users (Xiang et al., 2015; Shin et al., 2018). While exploratory in nature, this study offers a unique perspective in understanding users' online information processing behavior within the context of viewing online hotel reviews.

Also, this research further demonstrates the applicability of two-factor theory in the hotel context based on actual evaluations of hotel customers (Xiang et al., 2015). A considerable number of studies have argued that various hotel attributes could be conceptualized as either satisfiers or dissatisfiers (Albayrak & Caber, 2015; Barsky, 1992; Barsky & Labagh, 1992; Bodet et al., 2017; Cadotte & Turgeon, 1998; Ramanathan & Ramanathan, 2011; Robinot & Giannelloni, 2010; Slevitch et al., 2013). This suggests that the two-factor theory will likely remain a useful framework for understanding the hotel product for a number of benefits including service improvement and design. However, most studies have adopted a similar approach that relies on survey data to measure the discrepancy between expectations and perceived performance of attributes, and their findings are fairly similar to each other (Dolnicar, 2002; Heung, 2000). By utilizing real world data, this research sheds light on the nuances among various hotel attributes in association with guests' actual evaluation of their experiences.

7.2. Practical implications

This research reveals that interactions between review rating and text in hotel reviews can inform not only the consistency of the message but also the customer's perception of hotel experience. In this regard, hotels can find additional utilities of hotel reviews. While hotels usually measure the customer's overall satisfaction based on review rating or deal with customers' complaints by reading review text (Sparks & Bradley, 2017), now they can understand their current conditions in detail by considering interactions between review rating and text, and what kinds of expectations customers may have about specific attributes. Also, this research suggests that different perceptions of hotel attributes should be discussed based on hotels' location. In our research, why specific hotel attributes are more or less concerned by customers is attributed to the hotel's locations. In this way, as well as hotels, various hospitality and tourism businesses could utilize their online reviews more effectively.

Additionally, online review websites can develop their interface based on the current study's findings: Showing the major topics of the reviews by enabling reviewers to tag. In most social media platforms, users can set specific words as clickable tags by putting particular symbols, such as hashtags (#), and these tagged words are emphasized with different colors and formats. With the tagging function, writers usually highlight the major keywords of their content for readers to know what the content is about (e.g., #service, #staff, #location) (Tsur & Rappoport, 2012). We found that review helpfulness is differently perceived depending on which topics are frequently mentioned in high-rating or low-rating reviews. If reviewers tag the major topics of their reviews, readers can identify which hotel attributes are evaluated in the reviews at first glance and they can match the major topics with review rating. Like the voting system, the tagging function would enable users to easily sort out the reviews which include the information they want to know. For hotels, they can understand which aspects are primarily evaluated by their guests and how those aspects are generally evaluated. By adopting the tagging function based on the current study's findings, online review websites can provide more user-friendly interfaces for both individual and business users.

7.3. Limitations and future research

This study has several limitations. First, although we attempted to take measures (e.g., bootstrapping) to address issues resulting from using large data, the results must be interpreted with caution, because the significance of the regression results tends to be overestimated due to a large amount of data. Second, the proposed interaction effects were examined only with hotel reviews, which were collected only from a specific place, namely Manhattan, NYC. As such, the findings are context-based and limited in its generalizability. Furthermore, the current study focused on a few interaction effects (i.e., interactions between review rating and semantic feature, and linguistic feature). There are more interaction effects that deserve to be investigated for providing theoretical and practical implications. Third, some factors which are expected to affect the findings are not thoroughly controlled, including the differences between review websites and the age of the reviews (i.e., the time difference between the date of uploading reviews and the date of collecting or analyzing them). Although our findings and implications retrieved from various data sources might be widely applicable compared to those from a single source, the differences between the sources and the age of reviews are likely to affect the findings and implications. Future research needs to test the different interaction effects of review components and relationships between product attributes and the perceived information value of online reviews in a more "controlled" fashion.

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Table

Table 1. Hotel attributes identified through topic modeling.

Attribute 1: Value	Attribute 2: Landmark & Attraction	Attribute 3: Dining & Experience	Attribute 4: Core Product
Great	Square	Bar	Room
Location	Times	View	Free
Staff	Central	Trip	Bed
Good	Park	Restaurant	Small
Breakfast	Station	Service	Size
Nice	Building	Experience	Area
Place	Subway	Visit	Coffee
Excellent	Empire	Wonderful	Nice
Price	State	Lovely	Bathroom
Friendly	Broadway	Top	Shower

Table 2. Mean values of length, readability, and helpfulness score.

	TripAdvisor	Expedia	Yelp
Length (N of words)	56.5	23.8	59.7
Readability (0 ~ 100)	75.1	76.2	82.0
Helpfulness score (0 ~ 1)	0.18	0.15	0.16

Table 3. Moderated regression analysis.

Variable	Model 1		Model 2		Model 3	
	Original	Bootstrap	Original	Bootstrap	Original	Bootstrap
Star class	-0.001***	-0.025***	-0.001***	-0.005**	-0.001***	-0.006**
Attribute 1			0.033***	0.115***	0.037***	0.125***
Attribute 2			0.051***	0.198***	0.055***	0.209***
Attribute 3			-0.019***	-0.063***	-0.013***	-0.045***
Attribute 4			0.029***	0.107**	0.034***	0.122***
Length			0.060***	0.781***	0.060***	0.781***
Readability			-0.000***	-0.007**	-0.000***	-0.007**
Rating			0.011***	0.224**	0.011***	0.235***
Rating *Attribute 1					0.005***	0.022***
Rating *Attribute 2					0.008***	0.028***
Rating *Attribute 3					-0.002***	-0.012***
Rating *Attribute 4					0.005***	0.016***
Rating *Length					-0.001***	-0.013***
Rating *Readability					-0.000***	-0.003
R^2	0.001	0.001	0.567	0.561	0.570	0.563

Adjusted R^2	0.001	0.001	0.567	0.561	0.570	0.563
ΔR^2			F=18656***		F=101.44***	

Dependent variable: Review helpfulness (0-1).

Attribute 1: Value / Attribute 2: Landmark & Attraction / Attribute 3: Dining & Experience / Attribute 4: Core Product

*: $p < 0.05$ / **: $p < 0.01$/ ***: $p < 0.001$

Table 4. Comparative analysis of different models.

Variable	Original sample	Transformed sample
Star class	-0.0006***	-0.0008***
Attribute 1	-0.0365***	-0.0198***
Attribute 2	-0.0547***	-0.0440***
Attribute 3	-0.0128***	-0.0214***
Attribute 4	-0.0341***	-0.0303***
Length	-0.0595***	-0.2678***
Readability	-0.0000***	-0.0001***
Rating	-0.0114***	-0.0121***
Rating*Attribute 1	-0.0045***	-0.0057***
Rating*Attribute 2	-0.0078***	-0.0100***
Rating*Attribute 3	-0.0024***	-0.0025***
Rating*Attribute 4	-0.0051***	-0.0060***
Rating*Length	-0.0013***	-0.0104***
Rating*Readability	-0.0000***	-0.0000***
Adjusted R^2	0.5699	0.5211
AIC	-389197.7	-378473.7
BIC	-389045.5	-378321.6

Dependent variable: Helpfulness score (0-1).

*: $p < 0.05$ / **: $p < 0.01$/ ***: $p < 0.001$

Table 5. Post hoc analysis of different star class hotels (Regression results).

Variable	Model 1		Model 2	
	Budget (35,781)	Luxury (61,105)	Budget (35,781)	Luxury (61,105)
Attribute 1	0.032***	0.033***	0.036***	0.037***
Attribute 2	0.054***	0.050***	0.057***	0.054***
Attribute 3	-0.021***	-0.016***	-0.017***	-0.010***
Attribute 4	0.031***	0.029***	0.035***	0.034***
Length	0.057***	0.061***	0.057***	0.061***
Readability	-0.000	-0.000***	-0.000	-0.000***
Rating	0.012***	0.010***	0.013***	0.011***
Rating*Attribute 1			0.000	0.006***
Rating*Attribute 2			0.006***	0.008***
Rating*Attribute 3			0.002	-0.003***
Rating*Attribute 4			0.006***	0.005***
Rating*Length			-0.002***	-0.001***
Rating*Readability			-0.000*	-0.000***
Adjusted R^2	0.572	0.564	0.574	0.568
F	35773***	61097***	35767***	61091***
ΔR^2			F=23.89***	F=76.83***

Figure

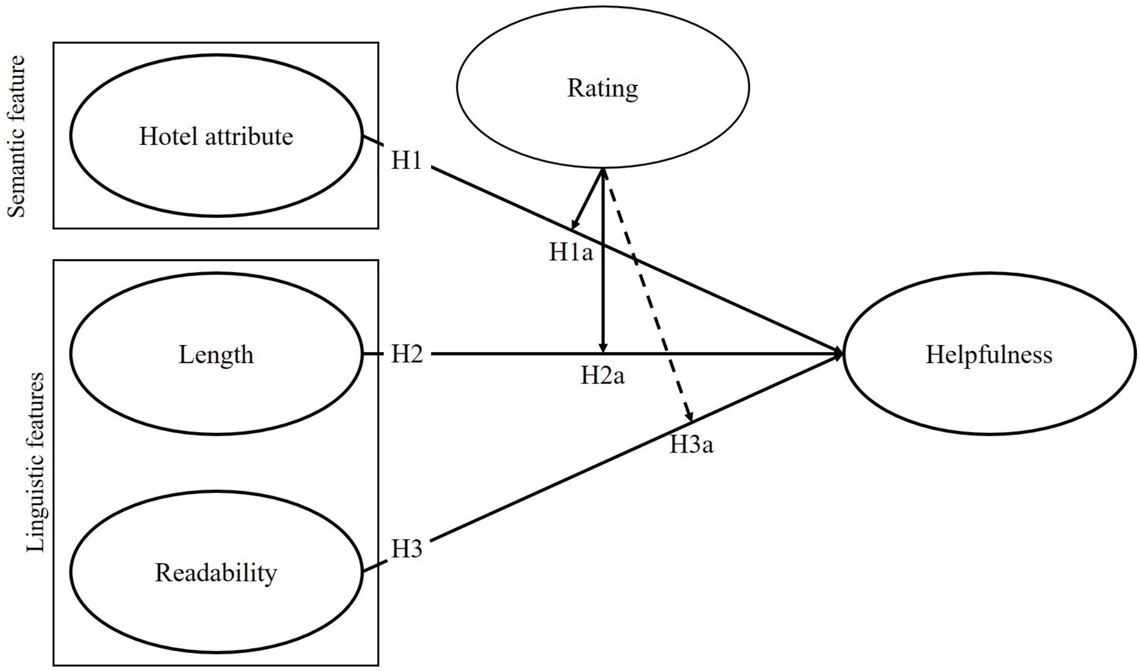

Figure 1. Research model