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Xun Xu,

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Does Traveler Satisfaction Differ in Various Travel Group Compositions?:

Evidence From Online Reviews

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Abstract

Purpose

This study aims to investigate the online customer review behavior and determinants of overall satisfaction with hotels of travelers in various travel group compositions.

Design/Methodology/Approach

We collected data from online reviews of travelers in various travel group compositions from 600 hotels in 100 of the largest cities in the United States from Booking.com and used latent semantic analysis (LSA) to identify the positive and negative factors from online reviews of travelers in various travel group compositions. Then we used text regression to determine the influential factors of overall satisfaction of travelers in various travel group compositions.

Findings

We found that not all the positive and negative textual factors mined from travelers' online reviews significantly influenced their overall satisfaction. In addition, the determinants of traveler satisfaction were different when travelers were in different travel group compositions.

Research Implications

We found similar online review behavior, but different basic, excitement, and performance factors of travelers in different travel group compositions.

Practical Implications

This study helps hoteliers understand customers' perception of the specific attributes of their products and services, which provides a guideline for businesses to design the priority rule to improve these corresponding attributes and use market segmentation strategy when dealing with customers in different travel group compositions.

Originality/Value

We examined and compared the online review behavior and determinants of satisfaction using the factors mined from online reviews between travelers in various travel group compositions. We combined customer ratings with textual reviews and predicted customer ratings from the factors extracted from textual reviews using LSA and text regression.

Keywords: customer satisfaction, online reviews, travel group composition, text mining, text regression

1. Introduction

Customers often post their reviews online after their hotel staying experience and share their experiences on various social media (Sotiriadis, 2017), which generates electronic word of mouth (eWOM) to influence potential customers' purchasing intention and behavior (Cantalops

& Salvi, 2014). Online reviews offer opportunities to examine customer satisfaction and dissatisfaction sources. Positive reviews indicate customer satisfaction, whereas negative reviews indicate customer dissatisfaction (Xu & Li, 2016). Compared with customer ratings, the open structure of textual reviews allows customers' consumption experiences and perceptions to be reflected more comprehensively and accurately (Xiang et al., 2015); thus, scholars have given more attention recently to textual reviews (e.g., Berezina et al., 2016; Xiang et al., 2015; Xu & Li, 2016). However, because of the frequent long length, substantial number, and open structure of online textual reviews, extracting key points from textual reviews can be complex and challenging and exacerbate information overload in the big data era (Gandomi & Haider, 2015).

Most of the previous studies examining online customer reviews of hotels have placed customers in a single group (e.g., Berezina et al., 2016), and research on online review behavioral comparisons between customers is lacking (Cantalops & Salvi, 2014). More research needs to be done to examine the online review behavior of customers from different backgrounds and on different kinds of trips (Cantalops & Salvi, 2014). This study fills the research gap by discussing the role of co-travelers on a leisure trip (i.e., travel group composition) in influencing travelers' online review behavior and the determinants of their overall satisfaction with hotels. Co-customers can affect customers' perception during the consumption experience through three social forces: immediacy, power, and number of co-customers (Miao et al., 2011). Travelers in different travel group compositions have different perceptions of the product / service quality because they have different needs and expectations (Ramanathan & McGill,

2007).

This study aims to investigate customers' online review behavior and determinants of overall satisfaction with hotels from the online textual reviews of leisure travelers in different travel group compositions. Specifically, two research questions served as guidelines: (a) what are the positive/negative factors extracted from reviews from travelers in each travel group composition regarding online review behaviors; and (b) which positive/negative factors positively/negatively influence travelers' overall satisfaction in each travel group composition regarding the determinants of overall satisfaction with hotels? We adopted of text-mining approach of latent semantic analysis (LSA) to extract and represent the textual factors from customers' positive and negative online textual reviews to answer the first question. We then designed a text regression model to evaluate the impact of various textual factors on customers' overall satisfaction to answer the second question. The main contribution of this study is that it compares the online review behavior and the determinants of satisfaction with hotels among travelers in various travel group compositions through their online reviews.

2. Literature Review

2.1 Determinants of Customer Satisfaction and Dissatisfaction With Hotels

Many previous studies have examined the determinants of overall customer satisfaction (e.g., Deng et al., 2013), which included the perception of products / services and value. The assumptions were that high performance in these areas enhances overall customer satisfaction whereas low performance decreases overall customer satisfaction. Few studies differed with

respect to the determinants of customer satisfaction and dissatisfaction (e.g., Zhou et al., 2014; Kim et al., 2016a). Zhou et al. (2014) found the determinants of customer satisfaction included location, staff, food, value, and the physical attributes of the room and hotel. Conversely, the determinants of customer dissatisfaction included poor cleanliness, high room cost, and poor employee language skills (Zhou et al., 2014).

Previous studies have also found that the determinants of customer satisfaction and dissatisfaction were influenced by the characteristics of the customers, including their demographic information (e.g., Mittal & Kamakura, 2001) and their reason for travel (Kashyap & Bojanic, 2000). Business and leisure travelers had different perspectives about the value, quality, and price of hotels (Kashyap & Bojanic, 2000). However, few studies have examined whether traveling with different people during leisure trips influences a traveler's perspective toward the hotels (e.g., Liu et al., 2013). Liu et al. (2013) found that differences existed in both customer expectations and satisfaction when the same traveler engaged in different travel group compositions. Our study extends Liu et al.'s (2013) work by examining the determinants of customer satisfaction and dissatisfaction among various travel group compositions through online reviews using LSA and text regression.

2.2 Analyzing Online Hotel Reviews

Today, with the high popularity of customer online reviews, more studies have explored customer satisfaction/dissatisfaction from online reviews (e.g., Berezina et al., 2016; Xiang et al., 2015). Online hotel reviews research was systematically reviewed in previous studies (e.g., Law

et al., 2009; Zanker et al., 2009; Kwok et al., 2017). Previous studies analyzing online hotel reviews focused on both content and writing style. Regarding content, previous studies (e.g., Berezina et al., 2016; Kim et al., 2016a; Xiang et al., 2015) examined the attributes of products and services customers frequently mentioned in their online reviews of hotels to examine the determinants of customer satisfaction and dissatisfaction with hotels. Regarding writing style, studies examined the discriminant word items (Dickinger et al., 2017), figurative and literal language style (Wu et al., 2017), and sentiment (Geetha et al., 2017) of online customer reviews. The methodologies examining online hotel reviews in previous studies included frequency analysis (Xiang et al., 2015), text-link analysis (Berezina et al., 2016), content analysis (Kim et al., 2016a), and topic modeling such as latent Dirichlet allocation (LDA; Guo et al., 2017).

Our study adopted the methods of LSA found in Xu and Li (2016). LSA combines rigorous statistical analysis techniques and scholarly judgment as it extracts and deciphers key latent factors (Kulkarni et al., 2014). The advantages of LSA over other text mining methods such as content analysis have been reflected theoretically and technically. Theoretically, the steps of LSA link to cognitive psychology theory, which reflects the acquisition, induction, and representation of knowledge (Kulkarni et al., 2014) and provides a good approach for understanding customer perception. Technically, LSA is especially suitable to deal with big data information overload because it does not need researchers to read the contents sentence by sentence. It is more objective because of its statistical and mathematical essence, which does not need researchers to do the subjective coding (Xu & Li, 2016). For customer online reviews, because they are written

in the form of natural language, it is possible that multiple words have similar meanings and topics may be not easily apparent. LSA handles the ambiguity of human languages well and can identify underlying concepts within textual data because it works in a manner quite similar to how the human brain distills meaning from text (Valle-Lisboa & Mizraji, 2007).

Recently, topic modeling such as LDA has also been used in hospitality contexts to study online customer reviews (e.g., Guo et al., 2017). Although topic modeling has a powerful function in identifying the insights of customers' perceptions under disclosed topics, it has a weakness in that the relationship between customer sentiment and the hospitality terms might be quite distant (Calheiros et al., 2017). In addition, LDA requires researchers to input the number of topics in order to create the LDA model (Yi & Allan, 2009). LSA can efficiently avoid these two weaknesses by extracting and representing human languages into certain factors, without the requirement of inputting the number of topics in advance but, rather, from analyzing the number of topics from its results.

We acknowledge that there are alternative methods for analyzing online reviews that can potentially include automated coding, such as rhetorical analysis and argument analysis (De Ascaniis and Gretzel, 2013), and discourse analysis (Vasquez, 2014). LSA, which is used in this study, does not rely on preconceived notions regarding topics from online reviews, thus limiting any subjective bias in the analysis (Kulkarni et al., 2014). LSA can discover hidden latent topics that facilitate modeling synonyms, detect multiple words that have similar meaning, and explain human language (Valle-Lisboa and Mizraji, 2007). LSA can extract the contextual-usage

meaning of words, thus providing information at the semantic level (Hossain et al, 2011). The quantitative features of LSA facilitate decision-making for business, and LSA has a wide range of applications in human language processing for any textual data such as online reviews and interview records (Lin et al., 2017).

2.3 *eWOM*

eWOM can be defined as any Internet-based informal communication between a perceived noncommercial communicator such as customers, which is often in the form of online reviews, online recommendations, and online opinions, with the contents' commenting on the usage or characteristics of products and services (Litvin et al., 2008). With the increased popularity of customers' online booking and online review behavior, studies about *eWOM* have developed quickly over the past decades. Compared with traditional word of mouth, *eWOM* has a faster spread speed and a broader spread range and can often show customers' perception of hotels in real time (Xu & Li, 2016). Previous studies focusing on *eWOM* can be categorized into two types: (a) those examining the generating factors and motivations of online reviews and (b) those studying the impacts of *eWOM* (Cantalops & Salvi, 2014). The motivations of customers who write online hotel reviews fall into four main categories. The first category of motivation, which is the strongest, is altruism to support the travel community. Bronner and De Hoog (2011) claimed that the most frequently mentioned motivation (70%) for writing online hotel reviews was to help other vacationers make better decisions about hotel choice. Helping businesses improve products and service quality also falls into this category of motivation (Bronner and De

Hoog, 2011). The motivations of altruism, reciprocity, and hedonic benefits are far more important than the motivators of vengeance and the need to vent (Yoo & Gretzel, 2011).

The second category of motivation is a customer's individual social needs and benefits. These include a customer's sense of belonging to the travel community (Cheung and Lee, 2012), social identification in the travel community (Cheung and Thadani, 2012), obtaining a reputation (e.g., through the votes of helpfulness of their posted reviews; Kwok and Xie, 2016), and anticipating hoteliers' online managerial response to their reviews (Gu and Ye, 2014).

The third category of motivation for writing online reviews is a customer's psychological needs, which are met by expressing his or her perceptions from their online reviews. Customers participating in online reviews want to show their satisfaction and commend hotels (Nusair et al., 2011), or they want to show their dissatisfaction and express their complaints, especially when service failures occur during their stay (Kim et al., 2009). Some customers obtain a sense of entertainment and enjoyment through writing and posting online reviews (Yoo and Gretzel, 2008).

The fourth category of motivation is economic incentives, which include receiving reward credits and having the chance to win gifts by posting feedback in online review platforms (Hennig-Thurau et al. 2004).

Regarding the impacts of eWOM, they include influencing customer trust, purchase intention, customer demand, and companies' financial performance (Xie et al., 2014). Our study falls into the first type: examining the online reviews generating factors and motivation, and the

online reviews' indication of customer perception such as satisfaction and dissatisfaction.

Although the generating factors of online reviews are well studied, research gaps exist in online review behavioral comparisons between customers (Cantallops & Salvi, 2014). More research needs to be done to explore the aspects that contribute to the generation of online reviews from customers with different cultural backgrounds and incomes as well as in different travel types and staying in different hotels (Cantallops & Salvi, 2014). Our study helps to fill the research gap by examining the comparison of the online review behavior and determinants of satisfaction among travelers in different travel group compositions.

2.4 Segmentation of Customer Online Reviews

With the rapid development of customer online reviews, some studies have focused on the segmentation of customer online reviews (e.g., Liu et al., 2017). These studies compared the segmentation of customer online reviews from various perspectives, but they are still limited and need to be further developed before they can become high-potential extensions (Cantallops & Salvi, 2014). These previous studies can be categorized into four types according to the segmentation. The first category of studies segments the online reviews by the writers (i.e., online customers). Among these few studies, Liu et al. (2017) examined the substantial differences of customers' online review emphasis on the hotels' various attributes, including room, location, cleanliness, service, and value between customers speaking different languages, including English, German, French, Italian, Portuguese, Spanish, Japanese, and Russian. Schuckert et al. (2015a) also examined a segment of online reviews by language groups. They

found different online rating behavior of English and non-English speakers for hotels. Our study followed this category of the research stream of segmenting online customer reviews by the writers (i.e., online customers in different travel group compositions). The second category of studies segments online reviews by the online platform (e.g., social media, online booking websites). For example, Xiang et al. (2017) compared the online reviews posted on various platforms, including Expedia, TripAdvisor, and Yelp. They found significant discrepancies in online reviews in terms of their linguistic characteristics, sentiment, semantic features, and usefulness. The third category of studies segments the online reviews by their influence. For example, Wu et al. (2017) found the influence of online reviews with a figurative language style on customers' attitude toward hotels was less than those with a literal language style. The fourth category of studies segments the online reviews by their comments on hotels. As an example, Xu and Li (2016) investigated online customer reviews of different types of hotels, and found the differences of the contents of the online reviews for different types of hotels.

3. Theoretical Background and Hypotheses Development

3.1 Customer Online Reviews Reflecting Their Satisfaction/Dissatisfaction

According to expectation disconfirmation theory (Oliver, 1980), the formation mechanism of customer overall satisfaction is mainly based on the comparison between customers' expectation of the product and services before consumption and the perceived quality of product and services after consumption. When the expectation meets or exceeds the perceived quality, customers are satisfied; otherwise, customers are dissatisfied (Churchill & Surprenant, 1982). According to the

three-factor theory (Füller & Matzler, 2008; Kano, 1984), factors involving product and service attributes are categorized into three types according to their influence on customer satisfaction/dissatisfaction: basic factors, excitement factors, and performance factors. Low performance regarding basic factors can generate customer dissatisfaction, yet their high performance does not generate customer satisfaction. High performance of excitement factors can generate customer satisfaction, yet their low performance does not generate customer dissatisfaction. The influence of performance factors is bidirectional: high performance can generate customer satisfaction, and low performance can generate customer dissatisfaction. According to multi-attribute theory (Ajzen, 1991), core attributes generally have a higher influence than do auxiliary attributes.

Customer online reviews reflect the authors' satisfaction and dissatisfaction with hotels (Berezina et al., 2016). However, other sources of motivation stimulate customers' behavior of posting online reviews, including their psychological needs (e.g., gaining social identity), having a sense of belonging to a community, and wanting to help companies and other customers (Cantalops & Salvi, 2014). In addition, the structure of online textual reviews is open, and content depends on many factors, such as the reviewers' educational background, emotion, supplier–customer relationship, tolerance and delight extent, expectation of response, reviewing time costs, and familiarity with the Internet (Schuckert et al., 2015b).

Customers posting positive textual reviews want to praise the products and services offered, make recommendations to future customers, and receive the positive effects of emotional

disclosure (Xiang et al., 2015). Therefore, the positive contents mentioned by the customers may not fully show customers' overall satisfaction with the product and service providers. Based on the preceding discussion, we propose:

H1: Not all positive textual factors significantly positively influence travelers' overall satisfaction.

Customers' negative textual reviews are often an outcome of a particular aspect of products and services failure (Xu & Li, 2016). This forms negative eWOM (Bradley et al., 2015). However, using attribution theory, Jiang et al. (2010) found that not all negative experiences lead to dissatisfaction. They found only a small portion of the variance of satisfaction can be found from the experiences customers mentioned.

The negative textual reviews showed the customers' disclosure of negative emotions to alleviate their embarrassment and frustration (Bradley et al., 2015). Many customers described the downside of the products and services to warn future customers or prompt the product and service provider to improve the quality (Cantalops & Salvi, 2014). The detailed description of negative textual reviews sometimes amplifies the downside of the products and services and can result in a discrepancy between the customer's perception and evaluation of the whole consumption experience (Kaltcheva et al., 2013). Customers' negative textual reviews therefore do not fully reflect customer overall satisfaction, which is determined by the comparison of expectation and perceived quality (Churchill & Surprenant, 1982). Based on the above discussion, we propose:

H2: Not all negative textual factors significantly negatively influence travelers' overall satisfaction.

3.2 Travel Group Composition

Travel group compositions (i.e., family travelers, couple travelers, group of friends, and solo travelers) influence customer expectation (Liu et al., 2013). The same travelers can have different motivations and travel styles when the travelers engage in different travel group compositions. This influences their expectations about products and services offered by hotels (Liu et al., 2013). Customers in different travel group compositions also have different perceptions of the quality of hotel products and services, which can be different from the actual quality (Berezina et al., 2016). Traveling with different partners causes travelers to have different emotions, which influence customers' attitudes and expectations concerning their experience (Price & Barrell, 1984). Travel group composition is a personal factor and serves as an important context influencing customers' evaluation of hotel products and services (Liu et al., 2013). This viewpoint can be reflected in their online reviews (Schuckert et al., 2015b).

Travelers in different travel group compositions can have different expectations about the products and services offered by hotels (Liu et al., 2013). Thus, according to expectation disconfirmation theory (Oliver, 1980), customers in different travel group compositions have different overall satisfaction levels. In addition, according to social impact theory (Latane, 1981), co-travelers can influence fellow customers through three social forces: (a) immediacy, which describes the temporal or spatial closeness of the co-travelers; (b) strength, which reflects the

power, importance, or intensity of the co-travelers; and (c) the number of co-travelers. Their interactions with co-travelers play an important role in customers' perceived quality (Ramanathan & McGill, 2007), arousing different felt and displayed emotions that can influence customers' overall satisfaction (Miao et al., 2011). Customer overall satisfaction is also influenced by affective attributes such as feeling comfortable and entertained and sensory attributes such as atmosphere, which are influenced by co-travelers (Kim & Perdue, 2013). Based on the preceding discussion, we propose the following:

H3a: The positive textual factors influencing satisfaction are different among travelers in different travel group compositions.

H3b: The negative textual factors influencing dissatisfaction are different among travelers in different travel group compositions.

4. Methodology

4.1 Data Collection

We collected online review data from Booking.com, one of the world's largest third-party hotel booking websites. Only the customers who booked through Booking.com could post reviews after their stay. Booking.com requests that customers post their positive and negative comments simultaneously, but separately. For each review, we collected both the positive side ("pros" portion of comments) and negative side ("cons" portion of comments) of the review. The advantage of collecting data from Booking.com is that the comments are already classified as positive or negative by the user. We examined the positive factors for the pros portion of the

reviews and the negative factors for the cons portion of the reviews. Overall customer satisfaction was shown numerically, ranging from 1 (worst) to 10 (best).

Based on Xiang et al.'s (2015) sample selection methodology, we collected the reviews from hotels in the 100 largest U.S. cities, according to the 2015 U.S. Census Bureau population estimate (US Census Bureau, 2015), including New York, Los Angeles, Chicago, and Houston. We sorted and filtered the hotels in each city based on their star level (0–5 stars). Doing this guaranteed that we collected an equal number of samples from each star-level hotel (i.e., 100 hotels for each star level). We believe this will control the effects caused by different hotel categories, and this resulted in 600 hotels in the 100 biggest cities. For each star level of hotel, we filtered all the reviews and kept only the reviews posted by U.S. customers in the leisure trip category. We believe this will control the effects caused by different travel purposes and cultural differences. Then, for each star level of hotel, we filtered the online reviews according to the travel group composition. Booking.com keeps online reviews from family travelers, couple travelers, group of friends, and solo travelers at each time. We randomly generated two numbers, which are denoted by a and b (ranged from 1–20). We then collected the review data according to these two numbers: namely, sample a in hotel b , which is based on the position of review and the position of hotel listed on Booking.com. We repeated this process twice for each travel group composition for each star level of hotel. In this way, for each star level of hotel, we have $100 \text{ hotels} \times 4 \text{ travel group compositions} \times 2 \text{ reviews}$, which equals 800 reviews in total. Because we have 6 star levels of hotels (from 0–5 stars), we collected 800×6 reviews, which equals

4,800 reviews in total. Among all of the reviews we collected, there were no missing values for information about the travel group composition because this is mandatory data input requested by Booking.com. However, we found that some of the review writers did not submit positive comments, negative comments, or both. Instead, they simply submitted the overall satisfaction score and demographic and travel information. We removed all such reviews in their entirety from the sample, which resulted in 2,887 efficient review samples with both a positive and negative portion of comments. These included 721 (24.97%) reviews from family travelers, 731 (25.32%) reviews from couple travelers, 709 (24.56%) reviews from those traveling with a group of friends, and 726 (25.15%) reviews from solo travelers. Fortunately, after removing the samples with missing pros / cons sections, we found there were approximately the same number of samples from each travel group composition for each star level of hotel. We believe this distribution of reviews will avoid the potential effects caused by travelers in certain travel group compositions who stay more frequently in certain types of hotels.

4.2 Research Method

We used text mining to examine customer online review behaviors by finding the positive and negative factors from their reviews, and we used a text regression approach to find the influence of these factors on their overall satisfaction. For each travel group composition, we used RapidMiner Studio, adopting three steps in invoking LSA (Kulkarni et al., 2014; Xu et al., 2017). The first step was preprocessing and term reduction. For each document containing online reviews, we removed “stop words” such as “the,” “is,” “a,” and “an” because they did not

contain meaningful information. In addition, term-stemming techniques, which can identify the word's root and regard all words with the same root (e.g., coordination, coordinating, coordinate) as one token, were applied to a word list. Moreover, we applied an n-gram algorithm identifying repeated phrases (e.g., comfortable room, friendly staff, walk distance) in the documents.

The second step is term frequency matrix transformation. All documents were converted into the term frequency by the document matrix in this step. We transformed the values in the matrix using a term frequency-inverse document frequency (TF-IDF) weighting method (Husbands et al., 2001).

The third step is singular value decomposition (SVD), with the purpose of reducing dimension. SVD computation has been introduced in detail in previous studies (e.g., Baker, 2005). SVD decomposes the TF-IDF weighted matrix and denotes matrix A into the production of three matrices: an orthogonal matrix X , a diagonal matrix Y , and the transpose of an orthogonal matrix Z . In detail, the relation between matrix A and matrices X , Y , Z is $A_{mn} = X_{mm}Y_{mn}Z_{nn}^T$, where $X^T X = I$ and $Z^T Z = I$. The orthonormal eigenvectors of AA^T compose the columns of matrix X , the diagonal $m \times n$ of matrix Y contains the square roots of eigenvalues from X or Z in descending order, and the orthonormal eigenvectors of $A^T A$ compose the columns of Z .

The interpretation of the LSA results is similar to the interpretation of the exploratory factor analysis (Kulkarni et al., 2014). We labeled each factor according to its high-loading terms and documents. After finding the positive and negative factors from reviews of each travel group

composition, we conducted the text regression process using vector space (Ngo-Ye & Sinha, 2014). For each travel group composition, the dependent variable was the customer rating indicating their overall satisfaction. The independent variables were the coordinates of each review vector space on each factor. (We separated positive and negative factors in two models.) Because the coordinates are orthogonal, there is no correlation between the independent variables. The flow chart in Figure 1 summarizes the methodology of this study.

-----< Insert Figure 1 About Here >-----

5. Results

5.1 Positive and Negative Factors of Reviews in Various Travel Group Compositions

The LSA identified positive and negative factors of reviews in various travel group compositions, as shown in Table 1. We selected the top 10 terms as the high-loading terms from the more than 1,200 terms contained in each of the factors for demonstration purposes. The LSA results indicated that these top factors cover more than 95% of all the unique terms and reviews, showing that these factors represent the contents of the online reviews of various travel group compositions. The singular value shows the extent of factor explains the variance (Baker, 2005). The higher singular value indicates the loading terms, and the corresponding attributes on the corresponding factor are discussed in more detail, as shown by the use of more words and phrases in customer online reviews. It is also important to note that certain phrases (e.g., bed_size) were determined based on the frequent co-occurrence through applying an n-gram algorithm identifying repeated phrases with two or three words. Certain phrases (e.g., slow_elev)

only contained the word's root because of the application of term-stemming techniques in LSA, which regards all words with the same root as one token, and we applied these to a word list.

-----< Insert TABLE 1 About Here >-----

5.2 Text Regression Results of Positive Factors

As shown in Table 1, the main textual factors of customers' positive reviews include room quality, staff service quality, and convenient location/easy access. However, the importance of these textual factors, indicated by the frequency of the words' appearance in these factors, is different, as shown by the singular values. In addition, factors such as valuable price, good view, and room amenities exist in certain travel group compositions.

Table 2 shows the textual regression results of the influence of each positive factor on overall satisfaction in each travel group composition. The dependent variable is the overall satisfaction of each customer, and the independent variable is the coordinates of each attribute mentioned by the corresponding customer in the vector space.

-----< Insert TABLE 2 About Here >-----

5.3 Text Regression Results of Negative Factors

Compared with the factors identified by LSA from the customers' positive reviews, more factors were identified from the negative reviews, and these negative factors are more specific and more diverse than the positive ones. The negative factors include poor staff behavior and attitude such as unfriendliness; facility and room issues such as old facility, uncomfortable bed, bathroom problems, dirty room, and poor room amenities; food issues such as a poor

breakfast; and operations issues such as noise, weak Wi-Fi, luggage-carrying problems, high charges, and smoking issues. The negative factors were different for each travel group composition. The high charges mainly indicates customers' perception of paying a high price, as shown by the top frequently used words and phrases (e.g., fee, pai_high, super_expens), indicating the expensive fees and room rates charged by hotels.

Table 3 shows the textual regression results of the influence of each negative factor on the overall satisfaction of each travel group composition. Table 3 shows that compared with positive factors, more diverse negative factors negatively influenced customer overall satisfaction.

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6. Discussion

6.1 Relationship Between Positive Textual Factors and Customer Overall Satisfaction

Using text regression, as shown in Table 2, our results support H1. Good value and good view are discussed in the textual reviews by family travelers and couple travelers, respectively. However, these two textual factors do not significantly positively influence customer overall satisfaction. One of the reasons for this is that the main function of positive textual reviews is to provide recommendations to future customers, showing the eWOM effect. Therefore, customers tend to describe their consumption experience more comprehensively in their textual reviews (Xiang et al., 2015). However, customer overall satisfaction reflects customers' evaluation of hotels, which is highly influenced by the core product and services (Yang & Mattila, 2012). This

result explains the asymmetric relationship between positive textual factors and the determinants of customer satisfaction.

6.2 Relationship Between Negative Textual Factors and Customer Overall Satisfaction

Using text regression, from Table 3, our results support H2. The insignificant negative textual factors include old facility in the family travel group composition; bathroom problems, and high charges in the group of friends travel group composition; a poor breakfast in the family and group of friends travel group compositions; and noise, weak Wi-Fi, and luggage-carrying problems in the couple travelers travel group composition. Posting negative reviews is a way for customers to release stress from certain service failures and warn future customers (Bradley et al., 2015). Most of the service failures in the hotel industry are the failures of certain detailed products and services (Lee et al., 2011). Only the core service failures have a major negative effect on customers' evaluation of hotels (Yang & Mattila, 2012). Customers' satisfaction can be restored when service providers take recovery actions such as compensation and commitment to improvements. These results explain the asymmetric relationship between negative textual factors and the determinants of customer dissatisfaction.

6.3 Travel Group Compositions

For each travel group composition, the positive determinants of customer satisfaction are different, which supports H3a. Although both room quality and friendly staff can significantly improve customer overall satisfaction for all travel group compositions, a convenient location and easy access play different roles in enhancing customer overall satisfaction in different travel

group compositions. Convenient location enhances customer satisfaction in all travel group compositions other than family travelers, and easy access only improves satisfaction of family travelers and group of friends. Hotel location mainly refers to the physical location, whereas access mainly refers to the transportation to and from hotels that is offered by hotels or by public or private transportation (Yang et al., 2014). Because more co-travelers are involved in family travel groups and group of friends, the access issue becomes more important for their accommodation. Easy access can save them time and effort when arriving at or departing from hotels and enhances their satisfaction. In addition, good room amenities such as furniture, bathroom amenities, and a refrigerator and microwave enhance solo travelers' satisfaction because of the enhanced convenience and perceived quality (Heo & Hyun, 2015).

Our results support hypothesis 3b. For family travelers, the negative determinants of overall satisfaction mainly involve the room amenities, including uncomfortable bed and bathroom, and noise. This result shows cognitive attributes, which refer to the quality of products and services that satisfy utilitarian needs and provide functional benefits, significantly influence family travelers' overall satisfaction (Juwaheer, 2004). For couple travelers, a dirty room and a poor breakfast were the main negative determinants of their overall satisfaction. This result shows the sensory attributes, which refer to the atmosphere and the arousal of emotion, highly influence couple travelers' overall satisfaction (Babin & Attaway, 2000). The failure of these attributes significantly reduces customer overall satisfaction. For a group of friends, an unfriendly staff and smoking issues were not tolerated. This result shows that a group of friends cares more about the

affective attributes, which relate to the comfortable feeling obtained from the perceived and imagined target (Cohen et al., 2008). Similarly, an unfriendly staff and smoking issues were included in the negative determinants, in addition to the unique negative determinant of poor room amenities of solo travelers. This result shows that unfriendly staff members and room amenities are performance factors that bidirectionally influence solo travelers' overall satisfaction.

Based on the text mining results in Table 1 and the text regression results in Tables 2 and 3, we created Table 4, which uses three-factor theory to show the different influence of basic factors, excitement factors, and performance factors on the overall satisfaction of customers in various travel group compositions. We mined all of the factors in Table 4 using LSA from online reviews.

-----< Insert TABLE 4 About Here >-----

As can be seen in Table 4, we extended the three-factor theory by adding one additional category: neutral factors, which are mentioned in the online reviews but do not influence customer overall satisfaction. Table 4 shows that the factors mined from online reviews from customers within various travel group compositions have high similarities, including staff behavior and attitude, facility and room amenities, food, and operations related products and service attributes. These results show the similarity of online review behavior by travelers in various travel group compositions because they commented on both core and auxiliary attributes of hotel products and services.

However, we found that the influence of these attributes (factors) on travelers' overall satisfaction was different in that the basic, excitement, and performance factors contained different attributes mentioned by travelers in different travel group compositions in their online reviews. This result confirms that travelers with the same backgrounds can have varied expectations of the various attributes of hotel products and services in different travel group compositions (Liu et al., 2013). Due to different expectations and needs of customers, the impact of these different attributes on customer satisfaction is different among them. Particularly, we found more negative factors than positive in the online reviews from customers in each travel group composition. However, many of these negative factors are neutral factors; thus, although they are mentioned frequently in customer online reviews showing their negative experience, these factors do not necessarily lead to customer dissatisfaction, which confirms Jiang et al. (2010). For example, although a poor breakfast is mentioned by family, couple, and group-of-friends travelers, it only leads to dissatisfaction for couple travelers. Comparatively, these neutral factors are more specific showing auxiliary service operations, and thus, they do not significantly influence customer perception.

7. Theoretical and Managerial Implications

7.1 Theoretical Implications

Our study examined the online review behavior and determinants of satisfaction from online textual reviews of travelers in various travel group compositions. We found multiple asymmetries. First, using LSA, we found that positive and negative textual factors were

asymmetric in customers' positive and negative reviews, confirming Berezina et al.'s (2016) findings that positive and negative reviews need to be studied separately to find the different aspects and attributes attracting customer attention.

Second, we found an asymmetric relationship between positive and negative textual factors and determinants of customer overall satisfaction, which reflects the separate cognitive process of customers writing textual reviews and customers' satisfaction /dissatisfaction with hotels. The contents and emphasis level of customer textual reviews are influenced by the motivation of eWOM and writing reviews (Cantallops & Salvi, 2014), writing style (Hu et al., 2012), emotion (Ullah et al., 2016), and sociability (Salehan & Kim, 2016). Although customers' satisfaction/dissatisfaction, as shown by the expectation disconfirmation theory (Oliver, 1980), is generated by the comparison between preconsumption expectation and the perceived quality of products and services, this study confirms that a negative experience does not always lead to customer dissatisfaction (Jiang et al., 2010) and that the motivation of spreading eWOM and writing online reviews is not just to show customer satisfaction and dissatisfaction (Cantallops & Salvi, 2014).

Third, we compared the positive and negative textual factors mined from online reviews from customers in different travel group compositions. We found that although travelers in various travel group compositions have similar online review behaviors, as shown by the textual factors mined from their reviews, based on the three-factor theory (Füller & Matzler, 2008; Kano, 1984), we found that the factors have different influences on the satisfaction of travelers in

various travel group compositions. This shows that travelers have different expectations and needs when in different travel group compositions (Liu et al., 2013). It also confirms social impact theory, showing the co-travelers' impact on customer perception.

In terms of information overload issues in the big data era, the LSA and text regression methods proposed in this study contribute to studies in which researchers explored the causal relationship between the key text factors identified in the textual data and the target research scale (i.e., satisfaction in this study). This study provides another example of using customer online textual reviews identifying customer perception and shows the business values of online reviews (Xie et al., 2014).

7.2 Managerial Implications

The significant business values of customer online reviews are mainly reflected in two aspects. First, the online reviews can help hoteliers understand customer perception toward their products and services and improve the corresponding attributes to better meet customer expectations and serve customer needs (Kim et al., 2016b). Second, the online reviews can generate eWOM, which influences customer trust, purchase intention, and hotel demand, and enhance hotels' financial performance (Cantalops & Salvi, 2014). Through mining the factors from online customer textual reviews and examining their relationship with customer overall satisfaction, our study supports the business value of customer reviews.

In the big data era, hoteliers face information overload from the high volume of data from customer reviews. Hoteliers can use the LSA proposed in this study to find the main factors in

customer online reviews that show the emphasis of customer comments on certain attributes of products and services. This process can help hoteliers to obtain the core contents of the majority of customers who write and care about hotels without reading each online review one by one.

LSA can be applied by business managers in two extended ways as well. First, managers can use LSA to explore customer textual reviews of other companies and identify their strengths and weaknesses from comparisons. They can also apply the benchmarking method. Second, managers can use LSA to explore customer textual reviews within a timeline. The comparison of textual factors and their corresponding relative emphasis level from customer online reviews in a timeline provides a way for managers to understand their improvement performance, changes in customer awareness, and the direction in which to conduct continuous improvement.

The LSA is feasible for hoteliers to utilize because it does not require a minimum sample number to analyze the textual data. However, the maximum number of factors extracted is less than or equal to the sample size (Kulkarni et al., 2014). According to previous studies (e.g., Xiang et al., 2015; Berezina et al., 2016), the number of hotel product and service attribute categories mentioned in online reviews is usually no more than 20. Therefore, 20 reviews for each category of travel group compensation should be enough for hoteliers to use LSA to analyze online reviews by customers. Some hotels have their own booking websites and online review platforms (e.g., Holiday Inn, Crowne Plaza, Candlewood Suites by IHG). Requiring customers to input all necessary information when they post online reviews can help hoteliers obtain reviews with no missing data.

The key factors mined from customer online reviews provide hoteliers with a guideline to implement corresponding improvements. Hotels usually face limited resources such as budget, labor, and materials. Our study found that not all product and service attributes mentioned by customers significantly influence their overall satisfaction. Thus, hoteliers can use the results of our study to design the priority rule to first implement the actions that correspond to the factors that significantly influence customer perception. The key factors, which might be given the highest priority, are performance factors because their influence is bidirectional: their high performance enhances customer satisfaction and the low performance generates customer dissatisfaction. As found in this study, the core product attributes such as room amenities and core service attributes such as staff attitude and behavior are among the performance factors.

Hoteliers should also pay attention to the role of co-travelers in travelers' overall satisfaction. Different relationships and the number of co-travelers influence the expectations and the needs of travelers toward a hotel's various products and services (Liu et al., 2013), and they therefore influence their overall satisfaction. Many hotels implement a market segmentation strategy that provides various products and services to different customers. From this study, hoteliers should understand that even the same customer, or customers with the same background, when in different travel group compositions can still have different influential factors leading to customer satisfaction. This situation amplifies the importance of personal factors in influencing traveler perception (Sigala, 2004) and provides insights for hoteliers in implementing customized products and services to travelers in different travel group compositions. Hoteliers can also

reposition their marketing and operations strategy depending on the majority of travelers in certain travel group compositions. For example, regarding places, hotels in certain regions might meet the need from the majority of travelers in certain travel group compositions. Regarding time, hotels might attract more family travelers at certain periods, and thus should target the product and service attributes that satisfy them.

Hotels can also use the eWOM effect from online customer reviews to attract more customers in various travel group compositions by improving the corresponding products and services. Creating an online forum and using social media provides more opportunities to spread eWOM. A hotel manager could also provide prompt responses to certain customer online reviews, especially extremely negative reviews, to demonstrate the hotel's commitment to improving its products and services and use eWOM to influence future customers' booking intentions (Gu & Ye, 2014). Hoteliers can also obtain customer perceptions from other channels such as feedback from comment cards. By taking care of the special needs of various travelers in different travel group compositions and using eWOM, businesses can better serve these travelers and enhance their satisfaction, which should lead to increased customer demand and improved corporate financial performance (Xie et al., 2014).

8. Conclusions, Limitations, and Extensions

8.1 Conclusions

Our study used text mining and text regression to examine online review behavior and the determinants of satisfaction of travelers in various travel group compositions. Our study has

three main conclusions.

First, the positive and negative factors mined from online reviews are different. More negative factors are mined from online reviews showing specific operations issues such as noise, weak Wi-Fi, and luggage-carrying and facility, and room amenities issues such as old facility, uncomfortable bed, and bathroom problems. Comparatively, the positive factors show more core attributes of hotel products and services such as room quality, friendly staff, and convenient location.

Second, an asymmetric relationship exists between textual factors identified by LSA and the determinants of traveler satisfaction identified by text regression. Not all identified textual factors from online customer reviews are the determinants of customer overall satisfaction, and there are more attribution biases in negative reviews than there are in positive reviews. Although specific operations issues such as weak Wi-Fi and luggage carrying are mentioned in online reviews, they do not necessarily lead to customer dissatisfaction.

Third, when comparing the textual factors and determinants of overall satisfaction of travelers in various travel group compositions, we found the textual factors are similar and include staff behavior and attitude issues, facility and room amenities issues, food issues, and operations issues. However, the role of these factors in influencing the overall satisfaction of travelers in various travel group compositions is different. Travelers in different travel group compositions have different basic, excitement, and performance factors from each other.

Particularly, specific operations issues such as noise, smoking, and bathroom cleanliness only

negatively influence overall satisfaction of travelers in certain travel group compositions. This shows the relationship closeness and number of co-customers influence the attributes of products and services customers care about and shows the impact of personal factors (i.e., travel group composition in our study) on customers' expectations, perceived quality, and perceptions.

8.2 Limitations and Future Research

This study has several limitations. First, we studied travelers' satisfaction in various travel group compositions: family travelers, couple travelers, group of friends, and solo travelers. However, the reasons causing the different perceptions of travelers' satisfaction in various travel group compositions might be due to not only the different travel group companions but also the travelers' age or life cycle. For example, family travelers might be older than solo travelers. With the limited customer demographic information of who posted the online reviews, due to anonymity and limited information about age, we did not control for age in this study. Future studies can test the influence of age on travelers' perception with the available age information. In addition, although we controlled the star level of hotels and the travel group composition by equally drawing the same number of samples of each type of travel group composition from each star level of hotels, we did not control the variables showing other properties of hotels such as chain/individual hotels. It is likely that the ownership structure of hotels could also influence travelers' perception (Jiang et al., 2014). Moreover, another limitation is: for each online textual review, we simultaneously collected both the positive comments (pros) and negative comments (cons) components. We analyzed the positive factors from the positive comments, and the

negative factors from the negative comments. However, these two components are nested in the same review with the same travel group composition. Because we sampled in a nested way, the observations are not independent, so the factor results for positive and negative comments are not independent. Future research can use other online booking platforms or social media platforms such as TripAdvisor to collect independent reviews from each travel group, thus avoiding this issue.

Future studies can also extend the current study by comparing the online review behavior and positive and negative determinants of overall satisfaction among customers with other personal factors such as gender, age, income, and educational background. In addition, textual processing methodologies can be applied to hotels' advertising information, hoteliers' replies to customer online reviews, and expert online reviews, which are other sources of eWOM that could influence customers' online purchase intentions.

REFERENCES

- Ajzen, I. (1991), "The theory of planned behavior", *Organizational Behavior and Human Decision Processes*, Vol. 50, No. 2, pp.179-211.
- Babin, B. J. and Attaway, J. S. (2000), "Atmospheric affect as a tool for creating value and gaining share of customer", *Journal of Business Research*, Vol. 49 No. 2, pp. 91-99.
- Baker, K. (2005), "Singular value decomposition tutorial", available at: https://www.ling.ohio-state.edu/~kbaker/pubs/Singular_Value_Decomposition_Tutorial.pdf (accessed 3 February 2016).
- Berezina, K., Bilgihan, A., Cobanoglu, C., and Okumus, F. (2016). "Understanding satisfied and dissatisfied hotel customers: text mining of online hotel reviews", *Journal of Hospitality Marketing and Management*, Vol. 25 No. 1, pp. 1-24.
- Bradley, G. L., Sparks, B. A., and Weber, K. (2015), "The stress of anonymous online reviews: a conceptual model and research agenda", *International Journal of Contemporary Hospitality*

- Management*, Vol. 27 No. 5, pp. 739-755.
- Bronner, F. and De Hoog, R. (2011). "Vacationers and eWOM: Who posts, and why, where, and what"? *Journal of Travel Research*, Vol. 50, No.1, pp.15-26.
- Calheiros, A. C., Moro, S., and Rita, P. (2017), "Sentiment classification of consumer generated online reviews using topic modeling", *Journal of Hospitality Marketing and Management*, in-print.
- Cantalops, A. S. and Salvi, F. (2014), "New consumer behavior: A review of research on eWOM and hotels", *International Journal of Hospitality Management*, Vol. 30, pp. 41-51.
- Cheung, C. M. K. and Lee, M. K. (2012), "What drives consumers to spread electronic word of mouth in online consumer-opinion platforms", *Decision Support Systems*, Vol. 53, No. 1, pp. 218-225.
- Cheung, C. M. K. and Thadani, D.R. (2012), "The impact of electronic word-of-mouth communication: a literature analysis and integrative model", *Decision Support Systems*, Vol. 54, No.1, pp. 461-470.
- Churchill, G. A. and Surprenant, C. (1982), "An investigation into the determinants of customer satisfaction", *Journal of Marketing Research*, Vol. 19 No. 4, pp. 491-504.
- Cohen, J.B., Pham, M.T. and Andrade, E.B. (2008), "The nature and role of affect in consumer behavior", in: Haugtvedt, C.P., Herr, P.M., Kardes, F.R. (Eds.), *Handbook of Consumer Psychology*, Taylor & Francis Group, New York, pp. 297-348.
- Dickinger, A., Lalicic, L., Mazanec, J. (2017), "Exploring the generalizability of discriminant word items and latent topics in online tourist reviews", *International Journal of Contemporary Hospitality Management*, Vol. 29 No. 2, pp.803-816.
- De Ascaniis, S. and Gretzel, U. (2013), "Communicative functions of online travel review titles: A pragmatic and linguistic investigation of destination and attraction OTR titles", *Studies in Communication Sciences*, Vol. 13, No. 2, pp.156-165.
- Deng, W. J., Yeh, M. L. and Sung, M. L. (2013), "A customer satisfaction index model for international tourist hotels: Integrating consumption emotions into the American customer satisfaction index", *International Journal of Hospitality Management*, Vol. 35, pp. 133-140.
- Füller, J. and Matzler, K. (2008), "Customer delight and market segmentation: An application of the three-factor theory of customer satisfaction on life style groups", *Tourism Management*, Vol. 29 No. 1, pp. 116-126.
- Gandomi, A., and Haider, M. (2015), "Beyond the hype: Big data concepts, methods, and analytics", *International Journal of Information Management*, Vol. 35, No. 2, pp. 137-144.
- Geetha, M., Singha, P., and Sinha, S. (2017), "Relationship between customer sentiment and online customer ratings for hotels-An empirical analysis", *Tourism Management*, Vol. 61, pp. 43-54.

- Gu, B., and Ye, Q. (2014), "First step in social media: measuring the influence of online management responses on customer satisfaction", *Production and Operations Management*, Vol. 23 No. 4, pp. 570-582.
- Guo, Y., Barnes, S. J., and Jia, Q. (2017), "Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent dirichlet allocation", *Tourism Management*, Vol. 59, pp. 467-483.
- Hennig-Thurau, T., Gwinner, K. P., Walsh, G. and Gremler, D. D. (2004), "Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the internet?", *Journal of Interactive Marketing*, Vol. 18, No. 1, pp. 38-52.
- Heo, C. Y. and Hyun, S. S. (2015), "Do luxury room amenities affect guests' willingness to pay?", *International Journal of Hospitality Management*, Vol. 46, pp. 161-168.
- Hossain, M. M., Prybutok, V. and Evangelopoulos, N. (2011), "Causal latent semantic Analysis (cLSA): An illustration", *International Business Research*, Vol. 4, No. 2, pp. 38-50.
- Hu, N., Bose, I., Koh, N. S. and Liu, L. (2012), "Manipulation of online reviews: An analysis of ratings, readability, and sentiments", *Decision Support Systems*, Vol. 52, pp. 674-684.
- Husbands, P., Simon, H. and Ding, C.H.Q. (2001), "On the use of the singular value decomposition for text retrieval", *Computational Information Retrieval*, Vol. 5, 145-156.
- Jiang, J., Gretzel, U. and Law, R., (2010). Do negative experiences always lead to dissatisfaction?—testing attribution theory in the context of online travel reviews. *Information and Communication Technologies in Tourism*, 2010, pp.297-308.
- Jiang, J., Gretzel, U., and Law, R. (2014). Influence of star rating and ownership structure on brand image of Mainland China hotels. *Journal of China Tourism Research*, 10(1), 69-94.
- Juwaheer, T.D. (2004), "Exploring international tourist' perception of hotel operations by using a modified SERVQUAL approach - a case study of Mauritius", *Managing Service Quality*, Vol. 14 No. 5, pp. 350-364.
- Kaltcheva, V. D., Winsor, R. D. and Parasuraman, A. (2013), "Do customer relationships mitigate or amplify failure responses?", *Journal of Business Research*, Vol. 66 No. 4, pp. 525-532.
- Kano, N., Seraku, N., Takahashi, F. and Tsuji, S., (1984). Attractive quality and must-be quality.
- Kashyap, R. and Bojanic, D. C. (2000), "A structural analysis of value, quality, and price perceptions of business and leisure travelers", *Journal of Travel Research*, Vol. 39 No. 1, pp. 45-51.
- Kim, B., Kim, B., Kim, S., Kim, S., Heo, C. Y. and Heo, C. Y. (2016a), "Analysis of satisfiers and dissatisfiers in online hotel reviews on social media", *International Journal of Contemporary Hospitality Management*, Vol. 28 No. 9, pp. 1915-1936.

- Kim, D. and Perdue, R. R. (2013), "The effects of cognitive, affective, and sensory attributes on hotel choice", *International Journal of Hospitality Management*, Vol. 35, pp. 246-257.
- Kim, T., Kim, W.G. and Kim, H.B. (2009), "The effects of perceived justice on recovery satisfaction, trust, word-of-mouth, and revisit intention in upscale hotels", *Tourism Management*, Vol. 30, No. 1, pp. 51-62.
- Kim, W. G., Li, J. and Brymer, R. A. (2016b), "The impact of social media reviews on restaurant performance: The moderating role of excellence certificate", *International Journal of Hospitality Management*, Vol. 55, pp. 41-51.
- Kulkarni, S. S., Apte, Uday M. and Evangelopoulos, N. E. (2014), "The use of Latent Semantic Analysis in operations management research", *Decision Sciences*, Vol. 45 No. 5, pp. 971-994.
- Kwok, L. and Xie, K. L. (2016), "Factors contributing to the helpfulness of online hotel reviews: Does manager response play a role?", *International Journal of Contemporary Hospitality Management*, Vol. 28, No. 10, pp. 2156-2177.
- Kwok, L., Xie, K. L. and Richards, T. (2017), "Thematic framework of online review research: A systematic analysis of contemporary literature on seven major hospitality and tourism journals", *International Journal of Contemporary Hospitality Management*, Vol. 29 No. 1, pp. 307-354.
- Latane, B. (1981), "The psychology of social impact", *American Psychologist*, Vol. 36, pp. 343-356.
- Law, R., Leung, R., and Buhalis, D. (2009), "Information technology applications in hospitality and tourism: a review of publications from 2005 to 2007", *Journal of Travel & Tourism Marketing*, Vol. 26, No. 5-6, pp. 599-623.
- Lee, M. J., Sing, N. and Chan, E. S. W. (2011), "Service failures and recovery actions in the hotel industry: A text-mining approach", *Journal of Vacation Marketing*, Vol. 17 No. 3, pp. 197-207.
- Lin, X., Li, Y. and Wang, X. (2017). Social commerce research: Definition, research themes and the trends. *International Journal of Information Management*, Vol. 37, No. 3, pp. 190-201.
- Litvin, S.W., Goldsmith, R.E. and Pan, B. (2008), "Electronic word-of-mouth in hospitality and tourism management", *Tourism management*, Vol. 29, No.3, pp.458-468.
- Liu, S., Law, R., Rong, J., Li, G. and Hall, J. (2013), "Analyzing changes in hotel customers' expectations by trip mode", *International Journal of Hospitality Management*, Vol. 34, pp. 359-371.
- Liu, Y., Teichert, T., Rossi, M., Li, H. and Hu, F. (2017). "Big data for big insights: Investigating language-specific drivers of hotel satisfaction with 412,784 user-generated reviews", *Tourism Management*, Vol. 59, pp.554-563.

- Miao, L., Mattila, A. S. and Mount, D. (2011), "Other consumers in service encounters: A script theoretical perspective", *International Journal of Hospitality Management*, Vol. 30, pp. 933 - 941.
- Mittal, V. and Kamakura, W. A. (2001), "Satisfaction, repurchase intent, and repurchase behavior: Investigating the moderating effect of customer characteristics", *Journal of Marketing Research*, Vol. 38 No. 1, pp. 131-142.
- Ngo-Ye, T. L. and Sinha, A. P. (2014), "The influence of reviewer engagement characteristics on online review helpfulness: A text regression model", *Decision Support Systems*, Vol. 61, pp. 47-58.
- Nusair, K., Parsa, H.G. and Cobanoglu, C. (2011), "Building a model of commitment for Generation Y: an empirical study on e-travel retailers", *Tourism Management*, Vol. 32, No.4, pp. 833-843.
- Oliver, R. L. (1980), "A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions", *Journal of Marketing Research*, Vol. 17, pp. 460-469.
- Price, D. D. and Barrell, J. J. (1984), "Some general laws of human emotion: Interrelationships between intensities of desire, expectation, and emotional feeling", *Journal of Personality*, Vol. 52 No. 4, pp. 289-409.
- Ramanathan, S. and McGill, A. L. (2007), "Consuming with others: social influence on moment-to-moment and retrospective evaluation of an experience", *Journal of Consumer Research*, Vol. 34 No. 4, pp. 506-524.
- Salehan, M. and Kim, D. J. (2016), "Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics", *Decision Support Systems*, Vol. 81, pp. 30-40.
- Schuckert, M., Liu, X. and Law, R. (2015a), "A segmentation of online reviews by language groups: How English and non-English speakers rate hotels differently", *International Journal of Hospitality Management*, Vol. 48, pp.143-149.
- Schuckert, M., Liu, X. and Law, R. (2015b), "Hospitality and tourism online reviews: Recent trends and future directions", *Journal of Travel and Tourism Marketing*, Vol. 32 No. 5, pp. 608-621.
- Sigala, M. (2004), "Reviewing the profile and behavior of internet users", *Journal of Travel and Tourism Marketing*, Vol. 17 No. 2-3, pp. 93-102.
- Sotiriadis, M. D. and Sotiriadis, M. D. (2017), "Sharing tourism experiences in social media: A literature review and a set of suggested business strategies", *International Journal of Contemporary Hospitality Management*, Vol. 29, No. 1, pp. 179-225.
- Ullah, R., Ambler, N., Kim, W. and Lee, H. (2016), "From valence to emotions: Exploring the distribution of emotions in online product reviews", *Decision Support Systems*, Vol. 81, pp.

41-53.

- US Census Bureau, Population Division. (2015), "Table 1: Annual Estimates of the Resident Population for Incorporated Places of 50,000 or More, Ranked by July 1, 2014 Population: April 1, 2010 to July 1, 2014 - United States -- Places of 50,000+ Population. 2014 Population Estimates", Available at: <http://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk> (accessed 8 October 2016).
- Valle-Lisboa, J. C., and Mizraji, E. (2007), "The uncovering of hidden structures by latent semantic analysis", *Information Sciences*, Vol. 177, No. 19, pp. 4122-4147.
- Vasquez, C. (2014), *The Discourse of Online Consumer Reviews*, Bloomsbury Publishing, New York, NY.
- Wu, L., Shen, H., Fan, A., and Mattila, A. S. (2017), "The impact of language style on consumers' reactions to online reviews", *Tourism Management*, Vol. 59, pp. 590-596.
- Xiang, Z., Du, Q., Ma, Y. and Fan, W. (2017), "A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism", *Tourism Management*, Vol. 58, pp.51-65.
- Xiang, Z., Schwartz, Z., Gerdes, J. H. J. and Uysal, M. (2015), "What can big data and text analytics tell us about hotel guest experience and satisfaction", *International Journal of Hospitality Management*, Vol. 44, pp. 120-130.
- Xie, K. L., Zhang, Z. and Zhang, Z. (2014), "The business value of online consumer reviews and management response to hotel performance", *International Journal of Hospitality Management*, Vol. 43, pp. 1-12.
- Xu, X. and Li, Y. (2016), "The Antecedents of Customer Satisfaction and Dissatisfaction toward Various Types of Hotels: A Text Mining Approach", *International Journal of Hospitality Management*, Vol. 55, pp. 57-69.
- Xu, X., Wang, X., Li, Y., and Haghighi, M. (2017), "Business intelligence in online customer textual reviews: Understanding consumer perceptions and influential factors", *International Journal of Information Management*, Vol. 37, No. 6, pp. 673-683.
- Yang, W. and Mattila, A. S. (2012), "The role of tie strength on consumer dissatisfaction responses", *International Journal of Hospitality Management*, Vol. 31, pp. 399-404.
- Yang, Y., Luo, H. and Lau, R. (2014), "Theoretical, empirical, and operational models in hotel location research", *International Journal of Hospitality Management*, Vol. 36, pp. 209-220.
- Yi, X. and Allan, J. (2009), "A comparative study of utilizing topic models for information retrieval", In *European Conference on Information Retrieval*, pp. 29-41. Springer Berlin Heidelberg.
- Yoo, K. H. and Gretzel, U. (2008), "What motivates consumers to write online travel

- reviews?”, *Information Technology & Tourism*, Vol. 10, No. 4, pp. 283-295.
- Yoo, K. H. and Gretzel, U. (2011), “Influence of personality on travel-related consumergenerated media creation”, *Computers in Human Behavior*, Vol.27, No.2, pp.609-621.
- Zanker, M., Jessenitschnig, M., and Fuchs, M. (2009), “Automated semantic annotations of tourism resources based on geospatial data”, *Information Technology & Tourism*, Vol. 11, No.4, pp.341-354.
- Zhou, L. Q., Ye, S., Pearce, P. and Wu, M. Y. (2014), “Refreshing hotel satisfaction studies by reconfiguring customer review data”, *International Journal of Hospitality Management*, Vol. 38, pp. 1-10.

Figure 1. Methodology of this study.

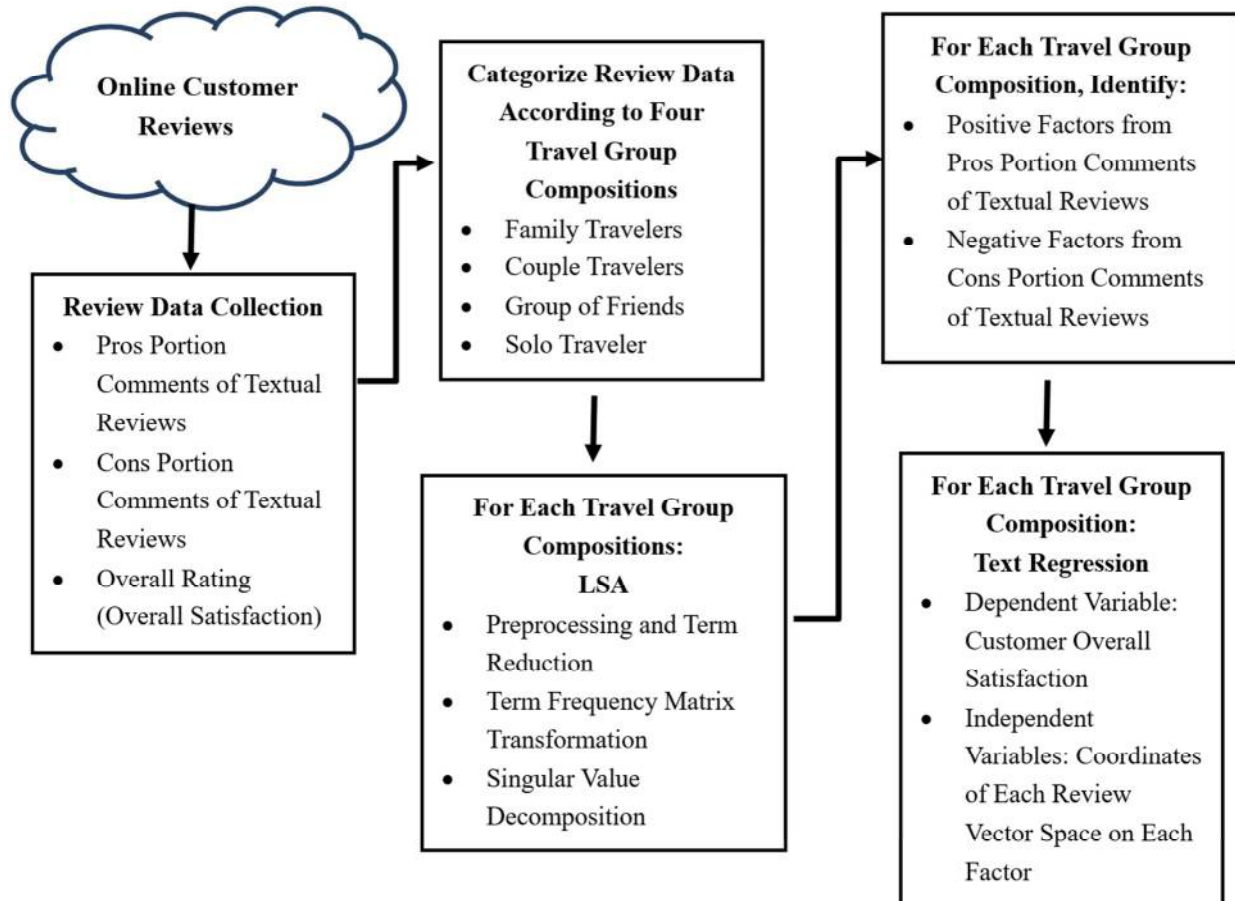


Table 1: Positive and Negative Factors from Online Reviews of Various Travel Group Compositions

<i>Online Reviews from Family Travelers</i>			
Factors	Interpretations (Labels)	Singular Values	High-Loading Terms
Positive Factors			
Factor 1	Friendly Staff	2.956	staff_friendly, staff_nice, desk, front, front_desk, friendly_help, staff_friendly_help, great_staff, staff_help, person
Factor 2	Easy Access	2.820	access, easy_access, airport, area, freeway, free_shuttle, shuttle_airport, station, easy, highway
Factor 3	Valuable Price	2.574	price, reason, good_price, reason_price, price_nice, worth, good_value, great_price, value_price, price_great
Factor 4	Room Quality	2.521	bed_comfort, good_room, comfort_great, comfort_room, nice_bed, big_room, clean, clean_big, comfort_good, room_spacious_bed
Negative Factors			
Factor 1	Noise	2.496	noisy, noise, loud, extreme_loud, air_condition, construct, ac, window, pool_area, street_noise
Factor 2	Uncomfortable Bed	2.246	uncomfort, bed_uncomfort, sleep, pull_bed, uncomfortable_pillow, bed_size, sheet, cover, king_bed, mattress
Factor 3	Bathroom	2.221	shower, towel, bath_tub, toilet, stain, bathroom, soap, hot_water, water_pressure, tub
Factor 4	Breakfast	2.119	Restaurant, continent_breakfast, continent, milk, breakfast_included, free_breakfast, egg, food, breakfast_horrible, cereal
Factor 5	Old Facility	2.093	elevator, update, old, light, hall, floor, out_date, lobby, facility, furniture, entrance
<i>Online Reviews from Couple Travelers</i>			
Factors	Interpretations (Labels)	Singular Values	High-Loading Terms
Positive Factors			
Factor 1	Convenient Location	2.876	convenient, easy_walk, good_location, location_great, walk, downtown, distance, walk_distance, convenient_location, location_excellent
Factor 2	Room Quality	2.781	bed_comfort, good_room, perfect_room, nice_bed, clean_good, room_big, room_size, room_great, bed_wonder, nice_room
Factor 3	Friendly Staff	2.550	staff_friendly, staff_friendly_help, friendly_help,

			help_staff, staff_profession, staff_help, ladi, courteou_help, staff_courteou, help_friendly
Factor 4	Good View	2.480	view, i_love, like_place, park_view, fantast, view_great, nice_view, beach, balcon_view, balconi_great
Negative Factors			
Factor 1	Wifi	2.236	wi-fi, free_wifi, weak, signal, wifi_work, bit_slow, disconnect, extrem_slow, network, slow
Factor 2	Breakfast	2.221	restaur, food_restaur, qualiti, free_breakfast, breakfast_area, breakfast_includ, eat_breakfast, breakfast_restaur, buffet, complimentari_breakfast
Factor 3	Luggage Carry	2.171	elev, elev_broken, slow_elev, carri_luggag, third_floor, luggag, stair, handicap, carri, heavi
Factor 4	Noise	2.095	loud, traffic, sound, construct, heard, road, lot_nois, sleep, traffic_nois, nois_night,
Factor 5	Dirty Room	2.073	horribl, smell, carpet, stain, room_clean, carpet_old, semlli, room_smell, mildew, wet
<i>Online Reviews from Group of Friends</i>			
Factors	Interpretations (Labels)	Singular Values	High-Loading Terms
Positive Factors			
Factor 1	Room Quality	2.945	bed_comfort, room_clean, nice_room, clean_room, clean_bed, clean_comfort, comfort_room, room_clean_bed, bed_comfort_room, love_room
Factor 2	Friendly Staff	2.706	friendly_staff, staff_nice, front_desk, staff_excel, front_desk_staff, friendly_help, staff_good, excel_help, great_friendly, welcom,
Factor 3	Convenient Location	2.640	locat_good, walk, distanc, conveni, conveni_locat, proxim, hotel_locat, minut, locat_great, perfect_locat
Factor 4	Easy Access	2.280	servic, airport, shuttl, shuttle_airport, shuttle_servic, free_shuttl_airport, easi_get, acess, shuttle_time, shuttle_bus
Negative Factors			
Factor 1	High Charges	2.499	expens, bit, super_expens, offer, monei, pai_room, fee, charg, pai_high, i_paid
Factor 2	Unfriendly Staff	2.414	front_desk, peopl, rude, horribl, person, staff_rude, maid, clerk, desk_clerk, housekeep
Factor 3	Smoke Issue	2.141	smell, smoke, smoke_room, smell_smoke, carpet, room_smell, stain, dirti, smell_smoke_room,

			cigarette
Factor 4	Bathroom	2.054	shower, water, hot, pressur, water_pressur, pressur_shower, poor_water, broken_tub, wash, drain
Factor 5	Breakfast	1.988	breakfast_limit, breakfast_poor, breakfast_area, coffe, restaur, waffl, poor_qualiti, varieti, continent, breakfast_choic, scrambl_egg
Online Reviews from Solo Travelers			
Factors	Interpretations (Labels)	Singular Values	High-Loading Terms
Positive Factors			
Factor 1	Friendly Staff	3.237	staff_friendly, friendly_help, friendly_staff, excel, nice_staff, staff_great, friendly_kind, staff_excel, staff_good, front_desk_staff
Factor 2	Room Quality	2.888	comfort, accomod, room_bed, spacious_room, room_nice, room_comfort, spacious_modern, comfort_clean, room_size, room_great
Factor 3	Convenient Location	2.488	locat_airport, conveni_locat, conveni, distanc, attract, convent_center, beach, station, park, downtown
Factor 4	Room Amenities	2.342	sofa, chair, pillow, microwav, fridg, air_condition, wall, closet, fridg_nice, room_light
Negative Factors			
Factor 1	Noise	2.312	nois, lot_nois, traffic, street, loud, car, traffic_nois, heard, train, hear_nois
Factor 2	Smoke Issue	2.263	smoke, smoke_room, smell, smell_smoke, non_smoke, i_smell_smoke, stai_smell, smell_cigarett, cigarett, smell_smoke_room
Factor 3	Unfriendly Staff	2.150	staff, rude, staff_front_desk, call_front_desk, disappoint, staff_unfriendly, staff_member, terribl, staff_rude, complain
Factor 4	Wifi	2.101	internet, connect, poor, wi-fi, internet_connect, slow_internet, charg_dai, addit_expens, slow_wifi, signal
Factor 5	Room Amenities	2.062	fridg, microwav, outdat, furnitur, heater, fan, coffe_machine, dryer, vacuum, hair_dryer

Table 2: Text Regression Results of Positive Influential Factors on Customer Overall Satisfaction With Hotels

Factors	Reflections	Textual Factors			
		Family Travelers	Couple Travelers	Group of Friends	Solo Travelers
Good Room Quality	comfort, spacious, clean	8.96**(4)	20.54*** (2)	7.36**(1)	22.57***(2)
Friendly Staff	friendly, helpful, courteous	8.81**(1)	16.16*** (3)	5.52**(2)	13.28*** (1)
Convenient Location	convenient, walk distance	N/A	20.24*** (1)	9.62**(3)	5.06**(3)
Easy Access	easy access, airport, station	14.04*** (2)	N/A	5.51**(4)	N/A
Good Value	good price, worth,	3.85(3)	N/A	N/A	N/A
Good View	fantastic view, great balcony, beach view	N/A	3.59(4)	N/A	N/A
Good Room Amenities	Sofa, chair, microwave, fridge, closet	N/A	N/A	N/A	5.98**(4)
<i>Intercept</i>	N/A	7.28***	7.10***	7.33***	7.52***

Remark:

- (1) Number in () shows the singular value ranking of each textual factor.
- (2) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Text Regression Results of Negative Influential Factors on Customer Overall Satisfaction With Hotels

Factors	Reflections	Textual Factors			
		Family Travelers	Couple Travelers	Group of Friends	Solo Travelers
Staff Behavior and Attitude Issue					
Unfriendly Staff	Front desk, staff, rude, complain	N/A	N/A	-28.94*** (2)	-5.55* (3)
Facility and Room Amenities Issue					
Old Facility	old, out-date, update, lobby, hall, entrance	2.14(5)	N/A	N/A	N/A
Uncomfortable Bed	uncomfortable bed, bed size, mattress	-7.74*** (2)	N/A	N/A	N/A
Bathroom Problems	shower, towel, toilet, water pressure, bath tub	-26.12*** (3)	N/A	3.04 (4)	N/A
Dirty Room	stain, mildew, carpet	N/A	-18.08*** (5)	N/A	N/A
Poor Room Amenities	Fridge, microwave, heater, fan, dryer	N/A	N/A	N/A	-5.47* (5)
Food Issue					
Poor Breakfast	milk, egg, cereal, limit variety, poor quality	-3.00 (4)	-12.95*** (2)	-1.62 (5)	N/A
Operations Issue					
Noise	Sound, loud, heard, street noise, traffic	-89.98*** (1)	-1.71 (4)	N/A	-5.49** (1)
Weak wifi	Network, Signal, weak, disconnection, slow	N/A	0.18 (1)	N/A	3.59 (4)
Luggage Carrying	Carry luggage, stair, slow elevator, heavy	N/A	2.46 (3)	N/A	N/A
High Charges	Fee, pay high, money, super expensive	N/A	N/A	3.29 (1)	N/A
Smoke Issue	Smoke, cigarette, smelly	N/A	N/A	-11.79*** (3)	-15.46*** (2)
Intercept	N/A	8.15***	7.62***	8.18***	7.93***

Remark:

- (1) Number in () shows the singular value ranking of each textual factor.
 (2) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: *Various Categories of Factors Influencing Customer Overall Satisfaction With Hotels*

Factor Category	Travel Group Composition			
	Family Travelers	Couple Travelers	Group of Friends	Solo Travelers
Basic Factors	Bed; bathroom; noise	Breakfast	Smoking issues	Noise; smoking issues
Excitement Factors	Room; staff; access	Staff; location	Room; location; access	Room; location
Performance Factors		Room	Staff	Staff; amenities
Neutral Factors	Value (p); facility (n); breakfast (n);	View (p); noise (n); Wi-Fi(n); luggage carrying (n)	Bathroom (n); breakfast (n); charges (n)	Wi-Fi (n)

Remark:

(p): This factor is mentioned in *positive* reviews, but it does not positively influence customer overall satisfaction.

(n): This factor is mentioned in *negative* reviews, but it does not negatively influence customer overall satisfaction.

Author Biography

Xun Xu holds a Ph.D. in Operations Management from Washington State University. He is currently an Assistant Professor of Operations Management in Department of Management, Operations, and Marketing in College of Business Administration at California State University, Stanislaus in United States. He teaches operations management, management science, materials and inventory management, and other operations management related courses. His research interests include service operations management, tourism and hospitality management, e-commerce, sustainability, and data and text mining. His papers appear on international journals, international conferences proceedings, and book chapters.