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# Exploring the impact of personalized management responses on tourists' satisfaction: A topic matching perspective

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ABSTRACT

As an online reputation management tool, hotel managers increasingly rely on management responses to online reviews to improve the electronic word of mouth (eWOM). Due to the substantial heterogeneity of textual reviews with different topics, it is particularly challenging to personalize the response for customer relationship management. Based on a panel data of 500 hotels in the state of Texas collected from TripAdvisor, this study examines the influence of personalized management responses on rating increase from a topic matching perspective. The empirical results show that (1) a high level of topic matching of management response leads to an increase of hotel online rating; (2) a high valence and a large variation of existing rating weaken the positive influence of such personalized management response; (3) the influence is stronger for economy hotels compared to luxury ones. Lastly, practical implications are provided.

## 1. Introduction

As a revolutionary technology popularized in the last decade, online reviews have substantially transformed the consumer decision-making process, especially in the tourism industry (Ladhari & Michaud, 2015; Litvin, Goldsmith, & Pan, 2008). Nowadays, service providers are able to leave responses to these online reviews, and tourism managers began to recognize the significance of their responding to online reviews. With the rapid growth of social media, service recovery typically takes the form of online management responses (Gu & Ye, 2014). Especially in the case of service failure, effective management responses are likely to protect the firm's reputation and reduce potential negative effects (Coombs, 2014). Customers may feel satisfied when receiving appropriate management responses from managers, which changes their attitude and evaluation of product and service. According to a TripAdvisor survey (2016), 85% of consumers believed that thoughtful management responses to negative reviews improved their impression of a hotel (an increase of 53% from 2013); 80% reported that seeing hotel management responses to reviews made them believe that the hotel cared more about them; 65% were more likely to book a hotel that responded to consumer reviews versus a comparable hotel which did not provide any management responses.

Prior scholars focused exclusively on effects of different response strategies, such as an apology, redress, facilitation, credibility, problem-solving, courtesy, explanations, acknowledge (Coombs, 2014; Davidow, 2003; Hui, 2007; Leung, Law, Hoof, & Buhalis, 2013; Sparks & Bradley, 2017). However, they largely overlooked the topic aspect of reviews and seldom considered an interaction between tourism managers and consumers (Mauri & Minazzi, 2013). In the real world, many hotel managers fail to pay close attention to consumers' reviews and just leave some 'standardized' responses in a haste, which may not match the comments from the customer. As shown in Fig. 1, a reviewer expressed dissatisfaction with an unreasonable cost in the review, and instead of dealing specifically with the price issue, the hotel manager made a simple apology, which fail to address only concerns by the reviewer. A typical example of topic-matched response can be found in Fig. 2, the Front Desk Supervisor asked the appropriate manager to solve the dining issue when the consumer complains about the breakfast, which representing a personalized management response according to the specific content of consumer reviews. On this basis, a couple of studies tried to examine the relationship between management response and consumer review, and its influence on customer evaluation. For example, Lee and Cranage (2014) showed that attitude consensus in online communication between managers and consumers played a pivotal role in influencing subsequent consumers' evaluation. Wei, Li, and Huang (2013) drawn into the correlational relationship between management response and customers' perceived sincerity and honesty. Nevertheless, only very few studies paid close attention to the

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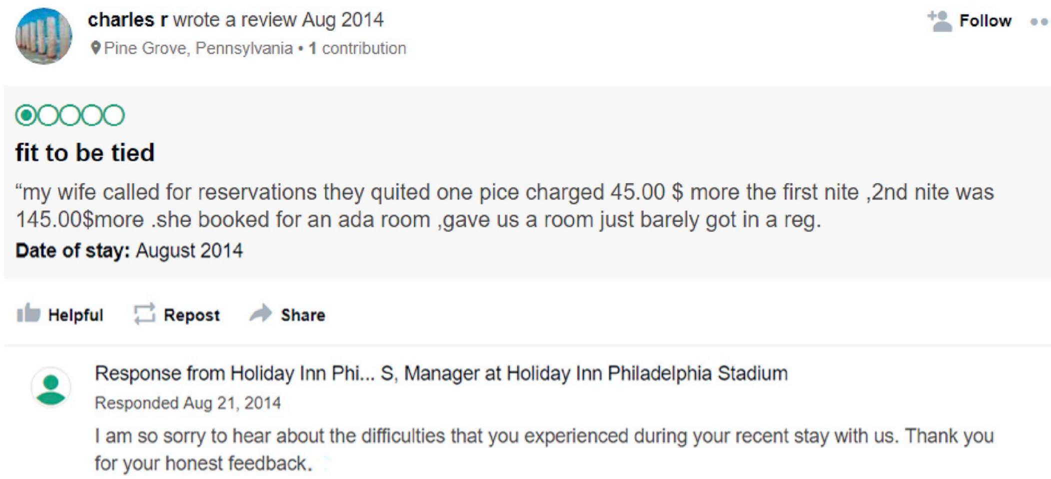


**Fig. 1.** Example of general response.

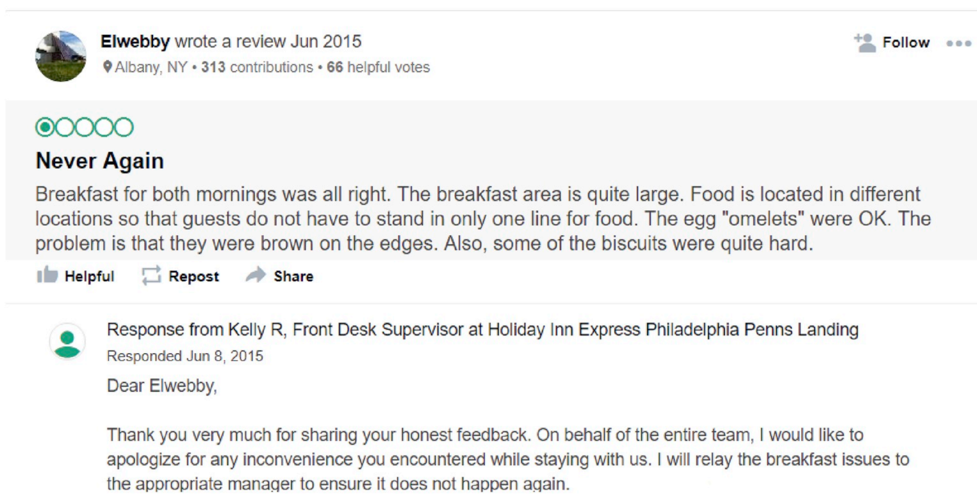


**Fig. 2.** Example of topic-matched response.

specific and personalized matching between management responses and the consumers' reviews.

To fill the above research gap, this study concentrates on personalized management responses and their effect on online review ratings of future customers. More specifically, we propose a topic-matching model to measure the degree of personalization of management responses. More topic-matched management responses show that hotel manager address more specific issues revealed in consumers' reviews and provided more relevant information and solutions that are relevant to these issues. Therefore, such personalized responses are expected to heighten future customers' perceived effectiveness of hotels' responses. This study utilizes a machine learning based text mining method for topic classification of online reviews and management responses then calculates the topic-matching degree of management response with the corresponding review. According to the analysis results of management responses in 500 Texas hotels, the average of topic-matching degree has just reached 40.5%, which means more than half of responses did not match the topic from the original posts. On this basis, this study further examines whether personalized management response has an influence on the rating increase and investigates its moderating effects. Evidence from previous studies showed that management response positively influences the online rating of products and service (Gu & Ye, 2014; Park & Allen, 2013; Ye, Gu, & Chen, 2010; Zhang & Vásquez, 2014), and ultimately leads to an increase in the sales of hotel (Ye, Law, & Gu, 2009; Öğüt & Taş, 2012; Yang, Park, & Hu, 2018). Therefore, our research results are expected to provide implications to hoteliers on their online reputation management strategies.

## 2. Literature review and research hypotheses

### 2.1. Literature review

#### 2.1.1. Online management response

Consumers post online reviews mostly due to their very satisfied or very dissatisfied experiences with the hotel service (Gu & Ye, 2014). Hotel managers can offer various types of compensation in their response to customer complaints, as a form of service recovery, ranging from financial compensation such as a discount for future services to social compensation such as an apology. Meanwhile, not just for negative reviews, online management responses to positive reviews also boost consumers' perceived fairness, satisfaction and repurchase intentions (Gu & Ye, 2014; Li, Cui, & Peng, 2018; Mattila & Cranage, 2005; Xie, So, & Wang, 2017). The efforts of adequate management responses not only can soothe the pain of dissatisfied consumers but also rein-force compliments and praise from the neutral and positive reviews (Lee & Cranage, 2014; Levy, Duan, & Boo, 2013; Xie et al., 2017).

Despite positive effect of management responses in general (Min, Lim, & Magnini, 2015; Ye et al., 2009), prior scholars also informed that it might be some negative effects of online management response in specific contexts. For example, Mauri and Minazzi (2013) found that the presence of management responses to consumer reviews has a negative impact on hotel booking intentions and consumer expectations. Xie et al. (2017) also argued that management responses with topic repetitions are negatively associated with the hotel's performance in the future. The limited number of previous studies showed that the impact of management responses is inconclusive, and this study contributes to the literature by understanding the effective and appropriate management responses posting from a topic matching perspective.

Some studies further demonstrated that strategies on response content that help managers to respond appropriately. Leung et al. (2013) stated that managers need to respon to relevant topics mentioned in the consumer reviews, such as explaining why something negative has occurred and how to improve it. Management responses should be semantically tailored to online reviews depending on the services offered and information covered in the customer review (Li et al., 2018) to avoid being too standardized and defensive. These studies investigated how to post appropriate responses, and focused on the specific content in consumer reviews. Different topics in consumers' reviews were summarized by prior studies including car parking, bathroom, dining, and location, which clearly and directly reflected the issue consumers "talking about" their accommodation experiences (Guo, Barnes, & Jia, 2017; Xiang, Schwartz, Jr, & Uysal, 2015). Xie et al. (2017) pointed that managers should react with new and constructive information such as specific service recovery solutions or actions rather than repeating the service failure descriptions in the consumer's online complaints because the repeating information is less likely to result in a cognitive fit and fail to help consumers identify the products. Instead of focusing on the specific content in new topics of responses, they advocated that managers should provide more different information topics to divert consumer's attention to other positive aspects of products or services. Wei et al. (2013) described specific management response addresses particular issues raised in consumers' reviews, while generic response has standardized content that is free from specific issues mentioned in the review. Compared with the generic responses, specific management responses show the hotel's sincerity toward consumers' issues and perform higher communication quality and trust level.

### 2.1.2. eWOM

Consumers always rely on electronic word of mouth (eWOM) from online reviews to get a better understanding of the service quality of the hotel before making purchase choices. Many studies have confirmed the eWOM's influence on the purchase decision and choice behavior (Bi, Liu, Fan, & Cambria, 2019a; Cui, Lui, & Guo, 2012; Fan, Xi, & Liu, 2018; Godes & Mayzlin, 2004; Lee & Youn, 2009; Litvin et al., 2008). Regarding online reviews, the valence (average) and variance of online rating are often regarded as the two most important eWOM factors on the Internet (Xie, Zhang, & Zhang, 2014). The valence of online rating usually indicates the overall evaluation of the hotel service (Goh, Heng, & Lin, 2013) whereas variance of online rating signals the heterogeneity in consumer opinions (Feng & Zhang, 2010; Sun, 2012).

Existing eWOM can largely shape hotels' management response strategies. Consumers are systematically more positive or negative in their reviewing behavior, and hotels' existing eWOM reflecting product quality may influence the emotional expression of consumers (Hong, Ni, Burtch, & Li, 2016). For instance, Xie et al. (2017) demonstrated that as the average review rating increases, the impact of management responses (i.e., job position of response providers, timeliness, and length of the response) varies on hotel financial performance. Using both empirical and theoretical analysis, Sun (2012) provided evidence that a high average rating indicated a high product quality and associated with a book's relative sales rank improvement.

As another eWOM measure, the variance of hotel rating expresses the fluctuation range of consumer's evaluations, which also has a significant influence on consumer's behavior (Feng & Zhang, 2010; Park & Park, 2013; Ye, Law, Gu, & Chen, 2011). The higher variance of rating signals different opinions among the consumers, that is, some consumers satisfy while others dislike (Sun, 2012). These consumer-generated reviews with higher variance may not be an unbiased indicator of low quality. Furthermore, when facing these reviews, consumers' perception of hotel quality and decision making may be affected disproportionately (Li & Hitt, 2008). A handful of scholars showed that the variance of rating has a positive impact on hotel performance and booking (Park & Park, 2013; Xie et al., 2014). However, in the meantime, a high level of eWOM variance indicates a high instability of service quality (Xie et al., 2014), which results in consumers take a skeptical attitude on the hotel. After all, consumers cannot neglect the problems that there are too many negative reviews indeed. Ye et al. (2009) found that the variance of the rating is negatively associated with hotel performance. Park and Park (2013) found that high variance of rating worsens the evaluation when reviewers have an unfavorable or negative expectation for the product before.

The impact of previously posted reviews on subsequent ratings has been recognized in extant literature (Guo & Zhou, 2016; Ho, Wu, & Tan, 2017). For example, Guo and Zhou (2016) demonstrated how two dimensions of prior rating, namely, volume and variance, influenced subsequent ratings. When it comes to the impact of management response and eWOM, we take two perspectives of repurchase intention and social influence. In one perspective, when the hotel experience is equal to consumers' expectation or obtaining satisfaction after the service recovery through received suitable management responses, they tend to have faith in the hotel's reputation and repurchase intention. In the other perspective, when the satisfaction of hotel experience and hotel management responses are much higher than consumers' expectation, consumers are more likely to recommend the hotel to their friends and relatives. At the same time, the social influence of prior consumer reviews and management responses might affect the opinion formation and expression phases of subsequent ones (Lee, Hosanagar, & Tan, 2015). The information in the prior consumers and their interactions with hotel managers profoundly shapes future consumers' expectation of hotel products and services, which will further reduce post-consumers selection biases before purchase. The impact of social influence is a function of the factors related to the gap between pre-purchase expectation and post-purchase evaluation. Specifically, an individual is more likely to leave a review when the magnitude of disconfirmation he/she encounters is larger. Incorporating such factors in our research can better explore management response and eWOM effect of previous reviews on subsequent reviews.

## 2.2. Hypothesis development

The personalized management response refers to the pertinence and compatibility between the response and the reviewer's concern. As one of the prominent characteristics, personalized management response has been examined in several previous studies. While there exist an inconsistent conclusions related to the impact of management response and eWOM on hotel sales performance (Xie et al., 2017), a number of studies reported the benefits associated with the consensus between responses and further behavior (Leung et al., 2013; Wei et al., 2013).

From a psychological perspective, a personalized management response might show the attitudinal consensus in online communication between managers and consumers. More topic-matched management responses indicate that hotel manager address more specific issues revealed in consumers' reviews and provided more relevant solutions. According to empathy theory, it provides individualized attention to customers; furthermore, empathetic responses with a high level of topic consensus can ease customers' anger and dissatisfaction by expressing that the manager understands their specific frustration and anger (Bauernfeind, 2009). Thus, such personalized responses are expected to play a pivotal role in attitudinal consensus for satisfaction development, which in turn influence subsequent consumers' evaluation.

Compared to standardized responses, such personalized responses are also expected to effectively heighten future customers' perceived effectiveness of hotels' responses. A topic-matched response tends to trigger appropriate information processing and efficient communication of review readers, which meets their functional needs (Garaus, Wagner, & Kummer, 2015; Gillespie, Muehling, & Kareklas, 2018; Kopp, Riekert, & Utz, 2018). For positive reviews, where consumers praise certain aspects of their experiences, hotel managers might focus on the specific topic and continue to respond to the corresponding advantages associated with the experiences. By doing this, they make potential review readers confirm the meritorious aspects and strengthen the intention to purchase. For the negative reviews, if consumers dissatisfy with a certain issue, the conscientious and problem-solving response make consumers feel hotel's concern and attention while hotel managers explain why the specific issue has occurred and promised how to improve it in the future. Additionally, a topic-matching between management response and consumer reviews might increase the perceived effectiveness and reduce potential perceived biases and cognitive cost for peer consumers as well (Lee & Cranage, 2014; Li, Cui, & Peng, 2017; Wei et al., 2013). Overall, there is a consensus that the topic discussed in the management response should be matched with the corresponding review. That is, a higher matching level of the topics communicated between management response and consumer review may lead to a positive impact on the rating. On this basis, we primarily focus on topic matching and propose the following hypothesis:

**H1.** The personalized management response with similar topics covered as the corresponding review has a positive impact on rating increase.

The rating valence has been viewed as a significant factor in improving consumers' perception of hotel quality and facilitating purchase decision-making (Nan, Pavlou, & Zhang, 2017; Sun, 2012). In the cognitive perspectives of dual-process theory, due to various resource constraints, eWOM valence that directly affects consumers' behavior can subsequently shrink the effect of personalized management responses on consumer's behavior during information processing (Filieri, 2015).

When posting an online rating after consumption, consumers often rely on the information both the level of quality or fulfillment and the peer consumers' rating. The quality is associated with their experiences during the real consumption, while the fulfillment is related to the peer consumers' review rating. In other words, consumers set a benchmark in their perception of hotel quality based on the eWOM valence and then form the expectation. If the quality reaches or exceeds the consumers' expectation, they will experience elation; otherwise, they will experience disappointment (Fan, Li, & Zhang, 2018). When it comes to tourism and hospitably industry, consumers in the lower rating hotel usually do not have high expectations on their experiences. If they feel dissatisfied with the service, a serious and relevant response from the manager will significantly weaken the negative effects; alternatively, if they feel satisfied with the service, an acceptable and relevant response from the manager will strengthen their satisfaction. However, consumers in the higher rating hotel are more demanding and always feel uncomfortable for service failure, even if the hotel has provided reasonable services (Ahluwalia & Gürhan-Canli, 2000). Therefore, the effect of personalized management response can be weaker for consumers in higher rating hotel. We propose the following hypothesis:

**H2.** eWOM valence negatively moderates the effect of personalized management response on rating increase.

As one of the prominent factors of online reviews, the eWOM variance can influence various attitudinal and behavioral outcomes of customers. While some studies did not conclude that inconsistency in the negative effect of eWOM variance (Feng & Zhang, 2010; Sun, 2012), most studies considered a higher level of eWOM variance as a dislike of the consumer in general except specific personality preference. Consumers are generally more likely to purchase a product/service with consensus reviews rather than extreme disagreement because the higher eWOM variance in product reviews indicates merely much-perceived uncertainty and perceived risk (Feng, Liu, & Fang, 2015; Meyer, 1981). Specifically, eWOM variance suggests some extreme negative online reviews, which provide more salient and conflicting information for consumer's value perception. Reviews variance signals the information quality signaling and therefore affects consumer's perceived source trustworthiness and credibility, as well as the subsequent information adoption of the source (i.e., the personalized response) (Filieri, 2015).

Moreover, consumers are more sensitive to negative reviews instead of positive cues in responses as suggested by the negativity bias theory (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Rozin & Royzman, 2001), and tend to pay more attention to avoid the potentially perceived uncertainty and perceived risk. Taken together, for hotels with dispersive ratings, consumers cannot disregard the extremely negative impact from the previous reviews and always cast doubts on the entire quality including the management response in general, while low eWOM variance might ultimately result in consumers' information adoption. As a result, the effect of personalized management response is weaker compared to hotels with less varied reviews. We propose the following hypothesis:

**H3.** eWOM variance negatively moderates the effect of personalized management response on rating increase.

The hotel grade represents the hotel's position in the hierarchy of hotel class, and among consumers, it reflects the long-term brand quality (Israeli, 2002). High-grade hotels with a higher price than economy hotels, usually known as luxury hotels, is the symbol of the high quality of service. Due to a variety of expense, consumers set up different expectations and requirements for different grades of hotels, in term of the predictive value, which refers to the ideal quality of a hotel they believe. Prior scholars pointed out that consumers tend to adjust their service expectation by different hotel grade. For example, Zhang, Ye, and Law (2011) divided hotels into three groups such as economy hotels, midscale hotels, and luxury hotels, and found that consumers expect higher hotel service for a high-grade hotel than a low-end hotel.

In this study, personalized management responses addressing particular issues reflect the hotel's sincere attitude toward consumers' issues, they also serve as the expectations of higher service quality perceived by consumers (Wei et al., 2013). For the enlightenment of utility function, the benefits from personalized management response may follow the law of diminishing marginal effect (Dermanov & Eklöf, 2001; Godes & Silva, 2012; Li & Hitt, 2008). The marginal utility of personalized management response is decreasing along with hotel grade, and a moderation effect of hotel grade is expected on personalized management response effort. For instance, an additional management response with topic matched should matter more for a rating increase in a hotel with a lower grade, than for those with a higher grade. This nonlinearity can be captured in a quadratic term. For luxury hotels, the higher price and higher brand equity are associated with more predictive quality. Considering hotels' brand and reputation, prospective consumers tend to get involvement based on their brands, and they are less likely to be influenced by management responses. In contrast, with little confidence in the brand, consumers in the economy hotel are more likely to rely on those personalized management responses. Li et al. (2017) also indicated that the strategy of management response is more useful for budget hotels than for premium hotels. Therefore, we propose the following hypothesis:

**H4.** Hotel grade negatively moderates the effect of personalized management response on rating increase.

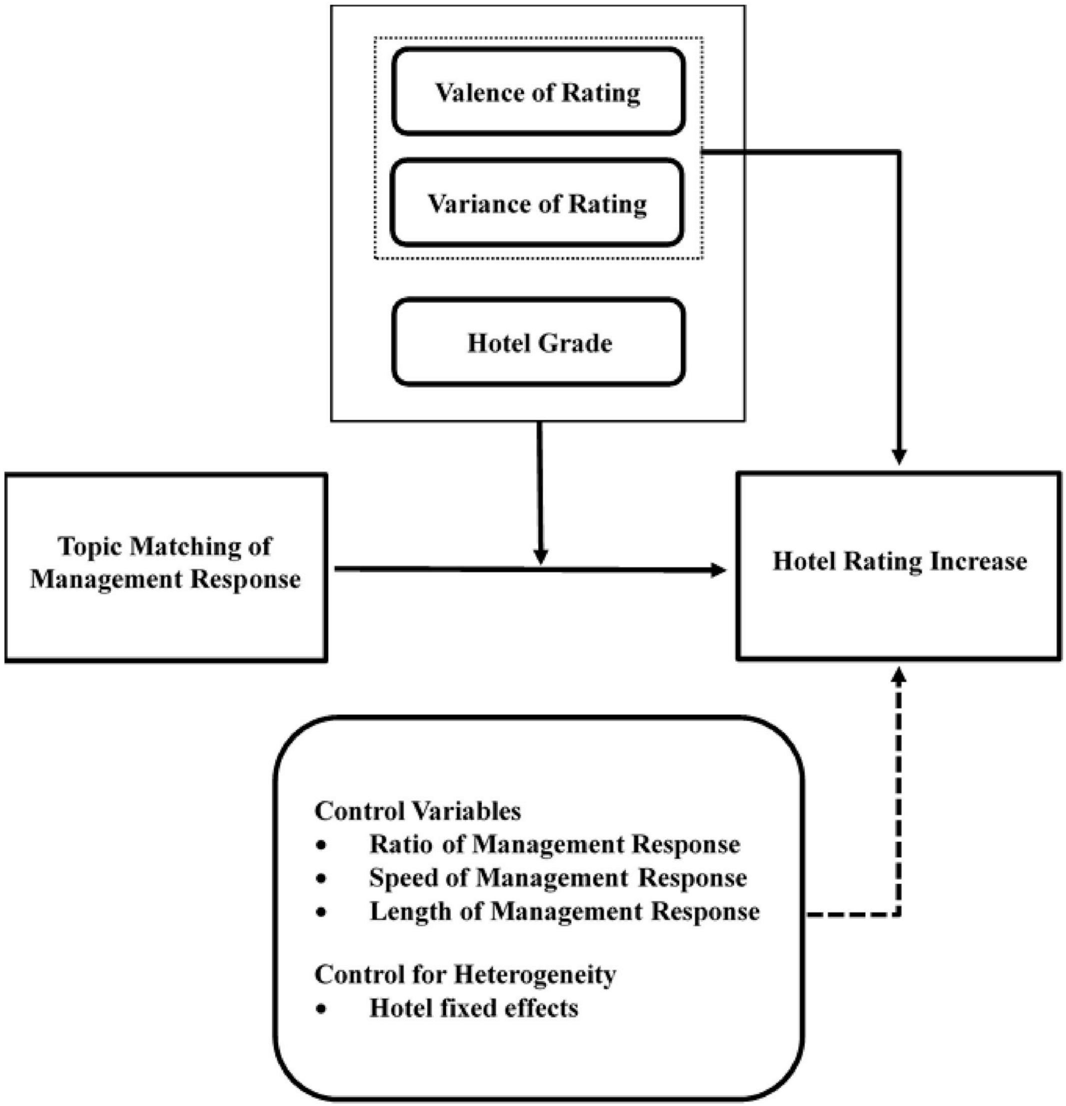


**Fig. 3.** Research framework.

Based on the above literature discussion and research hypotheses, we propose the following research framework (see Fig. 3).

## 3. Methodology

### 3.1. Data collection

We collected the hotel review data from TripAdvisor, one of the largest travel sites in the world, covering over 8 million accommodations with more than 702 million reviews and posts (TripAdvisor.com, 2018). It provides abundant data including online reviews, online ratings, management responses, and hotel information, and attracts many scholars to use its data for research in the tourism industry. TripAdvisor contains all the research elements we need, in particular, it designs a rating system allows every consumer give a rating with his or her review, which is easier for us to measure the average rating and rating increment of any period. Furthermore, we choose this site is also in consideration of good inheritance, association, and continuity with the previous excellent studies. Fig. 4 shows a screenshot of a hotel webpage on TripAdvisor.

Xie, Zhang, Zhang, Singh, and Lee (2016) found significant effects of managerial response on eWOM and hotel performance from the data of Texas on TripAdvisor, and Texas is the second largest state that owns a large number of hotels and consumer reviews on the site. Therefore, we also chose Texas as the target area and developed two crawlers to automatically download consumer reviews and hotel information on TripAdvisor from January 2013 to October 2016. Each review includes review text content, post time, and the overall rating on a range of one to five. If the review had a management response, we extracted the textual content of management response and response time of the hotel manager. In addition, we extracted grade (star rating) of each hotel, which is often used to indicate different types of hotel level from 1 to 5 (1 = economical to 5 = luxury). The initial dataset covered 500 hotels with 221,279 reviews after deleting the hotel without any consumer reviews. Table 1 displays the profile (i.e., the cities, location segment, operation, and size) of hotels based on the information obtained from Smith Travel Research (STR), a market research firm that provides data to the hotel industry (www.str.com). We processed the reviews of each hotel for a monthly basis, and the above data were aggregated to create a dataset in an unbalanced panel structure of hotel by month. Since this study focuses on the influence of personalized management response towards consumer review, we deleted hotel observations that did not receive any management responses in a single month. The final sample consists of 182 individual hotels with 4886 observations in six major hotel markets (Austin, Dallas, Fort Worth, Houston, San Antonio, and EI Paso) of Texas State in the United States. The distribution of online

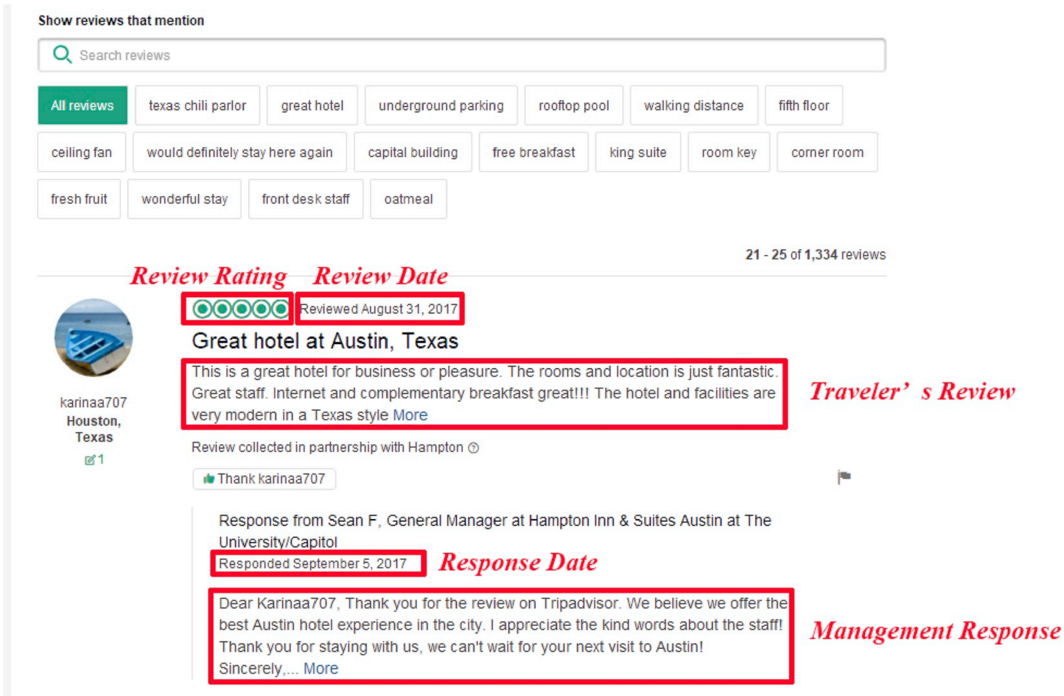


**Fig. 4.** Screenshot of TripAdvisor.

**Table 1**
Profile of sampled hotels.

| Cities | % | Location Segment | % | Operation | % |
|---|---|---|---|---|---|
| Houston | 27.63 | Urban | 42.15 | Franchise | 63.02 |
| San Antonio | 26.19 | Suburban | 34.71 | Chain | 23.76 |
| Austin | 16.91 | Airport | 19.22 | Independent | 13.22 |
| Dallas | 15.67 | Interstate | 2.89 | | |
| Fort Worth | 7.22 | Resort | 1.03 | | |
| El Paso | 6.38 | | | | |
| **Size** | **%** | **Hotel Grade** | **%** | | |
| < 75 Rooms | 13.81 | 1–1.5 stars | 0.6 | | |
| 75-149 Rooms | 49.07 | 2–2.5 stars | 33.4 | | |
| 150-299 Rooms | 23.3 | 3–3.5 stars | 48.2 | | |
| 300-500 Rooms | 10.1 | 4–4.5 stars | 16.4 | | |
| > 500 Rooms | 3.72 | 5 stars | 1.4 | | |

rating and hotel grade is shown in Fig. 5.

### 3.2. Research models

#### 3.2.1. Topic-matching degree

*3.2.1.1. Review topics.* In order to accurately summarize the representative topics in hotel reviews and management responses, we utilize the analysis of high-frequency feature words mentioned in consumer reviews (Alsumait, Barbará, & Domeniconi, 2008). On the outset, all the textual reviews totaling 221,279 texts were tokenized. After deleting some meaningless words (such as "I," "but," "is"), we obtained a list of top 200 high-frequency feature words to determine the representative topics. According to the attribute and meaning of these 'hot' words in the tourism industry, five types of the topic were clustered by text analysis, namely, food and beverage, price, facilities and amenities, service and environment. Appendix A respectively shows each topic, and its representative featured words. First, the

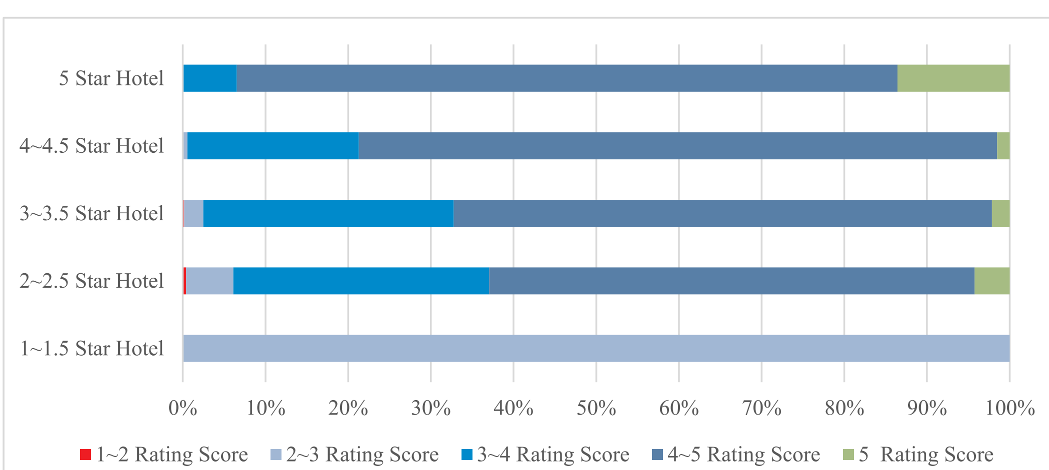


**Fig. 5.** Distribution of online rating and hotel grade.

topic of food and beverage involves comments, feedback, and issues about the dining, food, and drink in various locations of hotels, such as the dining room, on-site restaurant, bar, and cafeteria. Second, the price is one of the most important topics, and consumers often expressed their opinions on the cost of accommodation, the parking fee, and other relevant fees. The topic of price will increase rapidly, especially when the price fluctuates significantly, such as discounts activities. Third, the quality of the hotel's facilities and amenities represents the consumer's primary demand for lodging. Fourth, the topic of service includes service attitude and responsibility of hotel staff, which influenced the consumer's sentiment. Fifth, the environment is also a common factor in attracting consumers, such as location with convenient transportation, shopping mall, food plaza, and famous scenic spots. Unlike most prior studies only considering accommodation topics that were pre-determined by tourism websites such as room cleanness and sleep quality (Zhang et al., 2011), or an overwhelmed amount of scattered and meticulous topics (Guo et al., 2017). The five topics in this research represent the common "themes" that were obtained through the overall review corpus by consumers.

*3.2.1.2. SVM algorithm.* Recent years have witnessed an up-surging of applications of artificial intelligence (AI) technology, and text mining AI methods have been popular in analyzing important content and consumer satisfaction through online review texts, such as SVMs (Supported Vector Machines) classification model (Bi et al, 2019a, 2019b; Liu, Bi, & Fan, 2017). In order to calculate the topic matching degree of management response compared to the corresponding review, we first recognize which topic the text belongs, and SVMs was employed for classification of the topic from the consumer's textual reviews automatically. SVMs use hypothesis space of linear separators in a high dimensional feature space, trained with a learning algorithm from optimization theory (Scholkopf & Smola, 2002). SVMs seek a hyperplane that has the largest distance to the nearest training data point of any class. Considering the linear SVMs, a training dataset of n points are given by a tuple $(\overrightarrow{x_n}, y_n)$, where $y_n \in \{1, -1\}$ and it indicated the class to which the point $x_n$ belongs. The objective is to find a maximum-margin hyperplane that divides the group of points $x_n$ for which $y_n = 1$ from the group of points for which $y_n = -1$, which is defined so that the distance between the hyperplane and the nearest point $x_n$ from either group is maximized. If the training data are linearly separable, two parallel hyperplanes were selected that separate the two classes of data.

Geometrically, the distance between these two hyperplanes is $\frac{2}{\|\vec{\omega}\|}$, in order to maximize the distance between the planes we need to minimize $\|\vec{\omega}\|$, so the constraints can be described as follows:

$$\begin{cases} \overrightarrow{\omega_n} \cdot \overrightarrow{x_n} - b \geq 1, & if \;\; y_n = 1 \\ \overrightarrow{\omega_n} \cdot \overrightarrow{x_n} - b \leq -1, & if \;\; y_n = -1 \end{cases} \tag{1}$$

In addition to linear classification, SVMs can efficiently perform a non-linear classification using kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. The algorithm is formally similar with linear classification, except that each dot product is replaced by a nonlinear kernel function, which described by the following:

$$k(x_i, x_j) = \varphi(x_i) \cdot \varphi(x_j) \tag{2}$$

In summary, the obtained maximum-margin hyperplane from SVMs is capable of solving a binary classification problem effectively. Particularly, Multi-Class SVM will be constructed if the number of categories more than two, which can be considered as multiple binary classification problems. In this research, we tend to separate texts for five types of topic. Thus, Multi-Class SVM was adopted for topic classification.

*3.2.1.3. Data pre-processing.* In machine learning, SVMs were supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. On this basis, we make a training data set of 2500 consumer's review texts and manually marked them by topic types at the beginning (average of 500 texts per one topic). Appendix B shows examples of the training data set.

All English language-based reviews and management responses were pre-processed using three basic procedures: stemming, tokenization, and stop words removal. Since the words have the difference presentations between singular and plural, uppercase and lowercase, and tense, we performed the stemming process for each sentence to ensure accurate word extraction. Tokenization is a form of lexical analysis whereby a stream of text is broken up into words, phrases, or other meaningful elements called tokens (Xiang et al., 2015). In this study, each review was broken up into words using the Stanford CoreNLP Natural Language Processing Toolkit (Manning et al., 2014). Stop words refer to some meaningless and insignificance words and are usually filtered out before the processing of natural language data. We applied an existing stop word list consisting of 429 English words (Lextek.com, 2017), which has been widely employed in text mining and analytics (Xiang et al., 2015).

*3.2.1.4. Feature selection.* All the words constituted a dictionary after pre-processing of the training data set, and we choose several representative words as feature words to separate different topics. Multi-class classifiers are proposed to be developed by integrating the feature selection algorithm and the machine learning algorithm. Many popular feature selection methods have been advocated including document frequency, CHI statistics, information gain, gain ratio (Liu et al., 2017; Sharma & Dey, 2012; Tan & Zhang, 2008). Liu et al. (2017) stated that the gain ratio performed best among the four feature selection algorithms in multi-class sentiment classification. Meesad, Boonrawd, and Nuipian (2011) proved that CHI statistics with SVMs represents the best classification model compared to information gain and document frequency. To make sure our results are robust, we compared the experimental results of gain ratio and CHI statistics to determine the most appropriate feature selection algorithm. The introduction of each feature selection algorithm is given below.

CHI (chi-square statistic) is a popular and excellent method (Yang & Pedersen, 1997) in text classification based on the statistical test. According to equation (3), CHI value of each word was calculated and sort by heap algorithm in every type of topic, and we combine the sequence of feature words in each topic then obtained the feature vector. Each training text represented as a feature vector form to establish a classification model.

$$\chi^2(t, c) = \frac{N \times (AD - CB)^2}{(A + C) \times (B + D) \times (A + B) \times (C + D)} \tag{3}$$

where $N$ is the total number of texts in the training data set, $A$ denotes the number of texts which include the given word in current class, $B$ denotes the number of texts which include the given word in other classes (except current class), $C$ represents the number of texts which do not include the given word in current class, $D$ represents the number of texts which do not include the given word and are not in the current class.

In decision tree learning, the gain ratio is proposed in decision tree (C4.5) algorithms as a type of feature selection algorithm representing a ratio of information gains to the intrinsic information (Sharma & Dey, 2012). The calculation of gain ratio is based on normalizing the information gain value of the text feature. Information gain is also one of the most used feature selection algorithms, indicating the amount of information gained about a random variable or signal from observing another random variable. In the information gain algorithm, the importance of each text feature is measured according to the reduction of uncertainty if the value of the text feature is known (Liu et al., 2017).

Information gain is measured by the increase of the front and back information in the texts through the absence and existence of a certain feature word. The information gain (IG) value of a text feature can be calculated as follow:

$$\mathrm{IG}(t) = -\sum_{t=1}^{m} P(C_i)\log P(C_i) + P(t)\sum_{t=1}^{m} P(C_i|t)\log P(C_i|t) + P(\bar{t})\sum_{t=1}^{m} P(C_i|\bar{t})\log P(C_i|\bar{t}) \tag{4}$$

where $P(C_i)$ denotes the probability that text topic class $C_i$ occurs; $P(t)$ denotes the probability that text feature t occurs; $P(\bar{t})$ denotes the probability that text feature $t$ does not occur; $m$ denotes the total number of text topic classes. Given the fact that information gain may result in over-fitting problems, and gain ratio becomes an ideal alternative to information gain. In gain ratio algorithm, the split information for text feature $t$ is generated by splitting the data set $D$ into $v$ separations, where $v$ is the result of a test on the feature $t$. The split information of text feature $t$ is calculated as:

$$\mathrm{SplitInfo}(t) = -\sum_{j=1}^{v} \frac{|D_j|}{|D|} \times \log_2 \frac{|D_j|}{|D|} \tag{5}$$

where $|D_j|$ denotes the number of texts belonging to $|D|$. The gain ratio (GR) value is calculated as:

$$\mathrm{GR}(t) = \frac{\mathrm{IG}(t)}{\mathrm{SplitInfo}(t)} \tag{6}$$

We separately conducted the experiments on the above two feature selection algorithms based on the same classification model of SVMs. The training dataset and testing dataset are all 1000 textual reviews that were previously manually tagged. The experiments result showed CHI statistics with SVMs (classification accuracy of 70.2%) outperforms gain ratio with SVMs (classification accuracy of 68.7%) in the test dataset. Since different text samples and context may lead to different classification accuracy and results, we choose CHI statistics that are more suitable for this study as a feature selection algorithm.

*3.2.1.5. Calculation of Topic matching degree*. Given the satisfactory performance of SVMs in the multi-classification model (Bi et al., 2019a; Liu et al., 2017; Shang et al., 2007), we chose SVMs model and applied tmsvm package (a text mining system based SVMs) for text classification, which provided a text mining program with python edition (Zhang, 2017). In the modeling process, cross-validation was used to select the optimal parameter (c = 0.022, g = 32), and the classification accuracy reached 98.6% for the training dataset and 70.2% for the testing data, which is acceptable practically (e.g., Das & Chen, 2007; Pang & Lee, 2005; Liu et al., 2017). In order to understand the core meaning of consumer reviews, we first identified the most likely topic type that each review belongs to by this classification model. After that, we calculated the probability that management response and corresponding consumer review belong to the same topic type, which represented the topic-matching degree of management response (Fig. 6 shows the calculation framework of topic-matching degree based on SVMs). As the main independent variable in this research, $RespTM_{i,t}$ represents the average of above topic-matching degree for hotel $i$ in month $t$, which is described by the following:

$$RespTM_{i,t} = \frac{\sum_{j=1}^{n} RespTM_{i,t,j}}{n} \tag{7}$$

where $RespTM_{i,t,j}$ denotes the topic matching degree of the $j$-th management response for hotel $i$ in month $t$, and $n$ denotes the number of management responses for hotel $i$ in month $t$.

### 3.2.2. Other variables

The dependent variable is the rating increase of hotel $i$ in month $t$ ($RatingGR_{it}$), measured as the growth rate of rating average from month $t$-1 ($RevAvg_{i,t-1}$) to month $t$ ($RevAvg_{i,t}$), which is defined as follows.

$$RatingGR_{it} = \frac{RevAvg_{i,t} - RevAvg_{i,t-1}}{RevAvg_{i,t-1}} \tag{8}$$

According to some relevant previous literature, we controlled two factors of online reviews related and management response related. Online review-related controlling variables include the rating valence ($RevAvg_{i,t}$) and the variance of rating ($RevVar_{i,t}$) (Lin & Heng, 2015; Park & Park, 2013). Management responses related controlling variables include frequency of management response ($RespRatio_{i,t}$), the speed of management response ($RespInterval_{i,t}$) and length of management response ($RespLen_{i,t}$) (Li et al., 2017; Min et al., 2015). In particular, the speed of management response is measured by the duration between the review time and the response time, in the unit of the day. The detailed description of all variables in this study are shown in Table 2.

The descriptive statistics of all the variables is shown in Table 3. Specifically, the Standard deviation of $RespInterval_{i,t}$ and $RespLen_{i,t}$ are significantly higher than other variables, thus we take the logarithm of above two the variables in models to make overall data fluctuate more slowly and consistently. The correlation matrix is shown in Table 4. The correlation coefficients among all the independent variables are relatively small, which means the multi-collinearity problem of independent variables was eliminated in the estimation models.

### 3.2.3. Estimation models

A fixed-effects panel data model was applied to examine the effects of consumer reviews, management response, and consumer's ratings. Prior studies indicated that earlier reviews and management response usually influence consumer's behavior, the effects of word of mouth often carry over for several weeks (Trusov, Bucklin, & Pauwels, 2009). For example, Xie et al. (2016) used lagged one-quarter effect of management response on examining the hotel's reputation and performance. Therefore, we also examine lagged effect (i.e., previous one month) of management response on rating increase in the main model, and then the lagged time changed into previous one quarter in the subsequent robustness check. Moreover, in order to control the heterogeneity of different hotels, we use the fixed-effects estimation in this research. The estimation model was specified as follow:

$$RatingGR_{it} = \beta_0 + \beta_1 RespTM_{i,t-1} + \beta_2 RevAvg_{i,t-1} + \beta_3 RevVar_{i,t-1} + \beta_4 RespRatio_{i,t-1} + \beta_5 LnRespInterval_{i,t-1} + \beta_6 LnRespLen_{i,t-1} + \mu_i + \varepsilon_{it} \tag{9}$$

where a one-month lag of independent variables is specified; $\mu_i$ is the unobservable cross-section-specific effects; $\varepsilon_{it}$ is the usual disturbance term, which varies across hotels and time.

We further investigate the moderating effects of the eWOM and hotel grade (hypotheses 2 to 4) on the topic-matching degree of management responses. Similarly, the equation with three interaction terms is specified as follow:

$$RatingGR_{it} = \beta_0 + \beta_1 RespTM_{i,t-1} + \beta_2 RevAvg_{i,t-1} + \beta_3 RevVar_{i,t-1} + \beta_4 RespRatio_{i,t-1} + \beta_5 LnRespInterval_{i,t-1} + \beta_6 LnRespLen_{i,t-1} + \beta_7 RespTM_{i,t-1} * RevAvg_{i,t-1} + \beta_8 RespTM_{i,t-1} * RevVar_{i,t-1} + \beta_9 RespTM_{i,t-1} * HotelStars_i + \mu_i + \varepsilon_{it} \tag{10}$$

where $HotelStars_i$ denotes hotel grade for hotel $i$, which takes numerical value from 1 to 5 in the interaction term.

## 4. Empirical results

### 4.1. Main results

In the beginning, a Hausman test was carried out to determine whether the panel model use fixed-effects or random-effects (Hausman, 1978), the result shows that the Hausman test rejected the original hypothesis. Therefore, the fixed-effects specification is more suitable for the model in this research. Table 5 is the estimation results for the

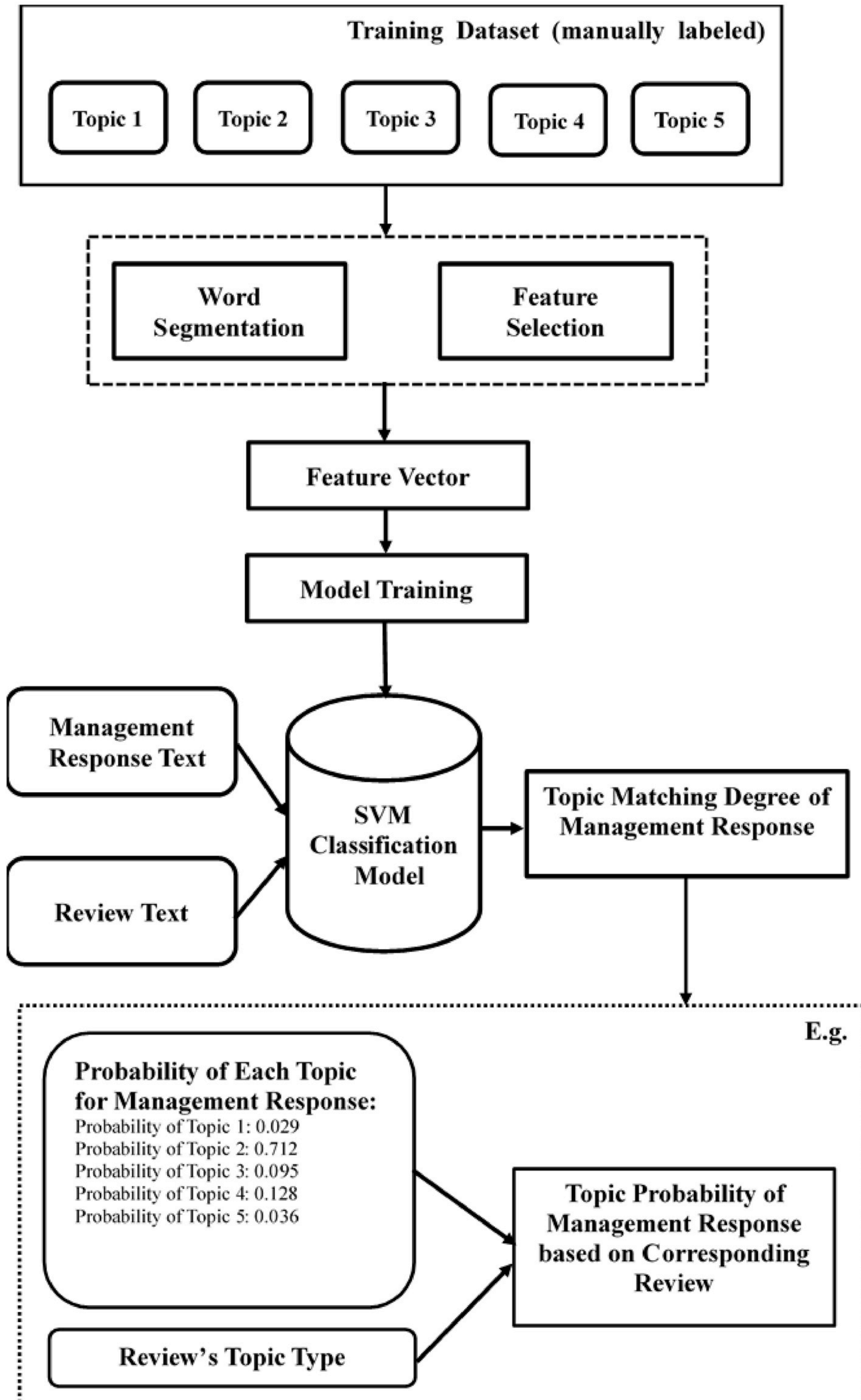


**Fig. 6.** Calculation of Topic-Matching Degree based on SVMs.

review and response data of previous one month. The results of Model 1 are estimated based on equation (9), and it indicates that the coefficient of $RespTM_{i,t-1}$ is positive and statistically significant (coeff. = 0.03493, $p < 0.01$). This means that the higher level of topic matching of management response is, the higher the hotel rating increase in next month is, and hypothesis 1 is supported. Regarding other variables, the coefficient of $RevAvg_{i,t-1}$ is significantly negative (coeff. = −0.27036, $p < 0.001$), thus the higher average of rating slows down the hotel rating increase. The coefficient of $RevVar_{i,t-1}$ is also negative (coeff. = −0.03319, $p < 0.001$), consumers still show negative attitudes on the hotel rating with larger fluctuations. The coefficient of $RespRatio_{i,t-1}$ is significantly positive (coeff. = 0.02982, $p < 0.001$), that is, hotel managers respond to more consumer reviews is helpful for improving hotel rating increase. The coefficient of $LnRespInterval_{i,t-1}$ is negative (coeff. = −0.00685, $p < 0.001$), it is interesting to see consumers feel satisfied with the faster response. The last coefficient of $LnRespLen_{i,t-1}$ is positive (coeff. = 0.01697, $p < 0.01$), which indicates that the longer response text allows consumers to perceive hotel

**Table 2**
Description of variables.

| Variables | Description |
|---|---|
| Dependent Variable | |
| *RatingGR*$_{it}$ | The growth rate of rating average from month $t$ to month $t$ for hotel $i$. |
| Independent Variables | |
| *RespTM*$_{it}$ | The average of topic-matching degree for hotel $i$ in month $t$ |
| *RevAvg*$_{it}$ | The average of review rating for hotel $i$ in month $t$ |
| *RevVar*$_{it}$ | The variance of review rating for hotel $i$ in month $t$ |
| Control Variables | |
| *RespRatio*$_{it}$ | The ratio of the number of management response to a number of reviews for hotel $i$ in month $t$ |
| *RespInterval*$_{it}$ | The average of duration (in days) between the review time and the response time for hotel $i$ in month $t$ |
| *RespLen*$_{it}$ | The average length of management response for hotel $i$ in month $t$ |

**Table 3**
Descriptive statistics of variables.

| Variables | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| *RatingGR* | 5315 | 0.008 | 0.159 | −0.778 | 3.8 |
| *RespTM* | 5456 | 0.411 | 0.162 | 0.001 | 0.998 |
| *RevAvg* | 5456 | 4.174 | 0.514 | 1 | 5 |
| *RevVar* | 5394 | 0.899 | 0.369 | 0 | 2.829 |
| *RespRatio* | 5456 | 0.747 | 0.312 | 0.011 | 1 |
| *LnRespInterval* | 5455 | 1.744 | 0.923 | −0.693 | 5.832 |
| *LnRespLen* | 5456 | 3.962 | 0.358 | 2.8 | 4.7 |
| *RespInterval* | 5456 | 9.990 | 19.332 | 0 | 341 |
| *RespLen* | 5456 | 55.858 | 18.811 | 16.444 | 110 |

manager's sincerity to some extent.

Model 2 further estimates the results of interaction terms (based on equation (10)), which shows that the moderating effects of $RevAvg_{i,t-1}$ (coeff. = −0.12322, $p < 0.001$), $RevVar_{i,t-1}$ (coeff. = −0.07318, $p < 0.05$) and $HotelStars_i$ (coeff. = −0.06739, $p < 0.001$) on $RespTM_{i,t-1}$ are all negatively associated with the hotel rating increase. First, both the variance and the average of hotel rating weaken the influence of topic matching of management response on hotel rating increase. Second, it is interesting that the influence of topic matching of management response on hotel rating increase is stronger in the lower-grade hotels. Thus, hypothesis 2-4 is supported.

Moreover, according to different results between the higher-grade and lower-grade hotel, a further test was performed that the two types of the hotel were respectively re-estimated with equations (9) and (10). The overall sample was divided into two groups: (1) 1–3.5 stars hotel were categorized as the lower-grade segment; (2) 4–5 stars hotel were categorized as the higher-grade segment. Models 3–6 in Table 6 show the estimation results of two groups, which indicates that all the variables and interaction terms in lower-grade hotels are statistically significant and consistent with models 1–2 in Table 5, and in contrast, the majority of variables and interaction terms in the higher-grade segment are non-significant. The finding further confirms that our main model is more suitable for a lower-grade hotel. Also, this test serves as a robustness check for hypothesis 4 from a different perspective.

### 4.2. Robustness check

Main empirical results presented above were based on monthly data of the reviews and response; to avoid the arbitrary choice of the time unit, we check the robustness of the results to different time unit that all variables were calculated by a quarter. We re-estimated empirical models with re-aggregated quarterly data, which uses precisely the same methods and equations as models 1–6. The results of re-estimation are shown in models 7–12 in Tables 7–8. In general, we find the same empirical results with regard to the main conclusions in chapter 4.1.

## 5. Discussion and implications

### 5.1. Discussion

In today's online social media environment, consumers are giving increasing weight to communication quality, and effective online management response becomes a key channel for managers to interact with current consumers and demonstrate a good communication quality to future consumers (e.g., Xie et al., 2014). Previous studies pinpointed that an appropriate management response should relate to the specific content contained in the consumer reviews (e.g., Wei et al., 2013); yet, little is known about how these personalized management responses influence customer satisfaction and how effective they are. Our study presents a pioneering research effort from a new perspective of text mining and reveals that the usefulness of topic-matched management response on future hotel online reputation. The findings also support a positive relationship among online rating, decent communication quality and service trustworthiness perceived by consumers (Fan & Zheng, 2006). Although we summarized five types of hotel topics from TripAdvisor reviews and analyzed the influence of this topic matching relationship on eWOM, such personalized matching effect may shape different consumer perceptions between each topic. Thus, we investigate which topic(s) would be more effective than others. On this basis, we separately estimated the influence of topic matching degree on rating increase under the five topics according to equation (9), and their coefficient and 95% coefficient intervals as shown in Fig. 7. The results indicate that personalized responses to service topics had a larger effect than to other topics (see the result of Table 9), which indicates consumers are more sensitive to topic-matched management response concerning ‘service’ communication and attitudes.

More importantly, we also show the moderating effects of valence and variance of online rating on the influence of personalized management responses. First, for hotels with high eWOM valence, the influence of personalized management response on hotel rating increase is weaker than for hotels with low eWOM valence. The result can be explained that positive information usually indicates more expectation and diagnostic, which may lead consumers to pay more attention to service contrast and weaken the effects of management responses. In addition, the variance of rating also negatively moderates the effects of personalized management response on hotel rating increase. The research suggested that consumers may be entangled with the relatively negative reviews when facing the higher variance of rating, and the effects of management responses on satisfaction become less significant.

Few scholars discussed the impact of hotel grade on online

**Table 4**
Correlation matrix of variables.

| | *RatingGR* | *RespTM* | *RevAvg* | *RevVar* | *RespRatio* | *LnRespInterval* |
|---|---|---|---|---|---|---|
| *RespTM* | 0.0313 | | | | | |
| *RevAvg* | 0.3937 | 0.0196 | | | | |
| *RevVar* | −0.2596 | 0.0183 | −0.6959 | | | |
| *RespRatio* | 0.0176 | 0.0042 | −0.0544 | −0.0189 | | |
| *LnRespInterval* | 0.0159 | −0.0293 | −0.0798 | 0.0411 | 0.0035 | |
| *LnRespLen* | −0.0811 | 0.1195 | −0.099 | 0.0469 | −0.1875 | −0.0804 |

**Table 5**
Estimation results by month with all sample.

| *RatingGR* | model 1 | model 2 |
|---|---|---|
| | all sample | all sample |
| *RespTM* | 0.03493** | 0.03512** |
| | (0.01079) | (0.01078) |
| *RevAvg* | −0.27036*** | −0.27145*** |
| | (0.00516) | (0.00516) |
| *RevVar* | −0.03319*** | −0.03505*** |
| | (0.00608) | (0.00608) |
| *RespRatio* | 0.02982*** | 0.03024*** |
| | (0.0072) | (0.00719) |
| *LnRespInterval* | −0.00685*** | −0.00672** |
| | (0.00205) | (0.00205) |
| *LnRespLen* | 0.01697** | 0.01745** |
| | (0.00628) | (0.00626) |
| *RespTM*RevAvg* | | −0.12322*** |
| | | (0.03301) |
| *RespTM*RevVar* | | −0.07318* |
| | | (0.03632) |
| *RespTM*HotelStars* | | −0.06739*** |
| | | (0.01569) |
| Constant | 1.075*** | 1.079*** |
| | (0.03876) | (0.03870) |
| Observations | 4886 | 4886 |
| R-squared | 0.46588 | 0.46943 |
| Adj R-squared | 0.44498 | 0.44832 |

Standard errors in parentheses.
*p < 0.05, **p < 0.01, ***p < 0.001.

**Table 6**
Estimation results by month with different hotel grades.

| *RatingGR* | model 3 | model 4 | model 5 | model 6 |
|---|---|---|---|---|
| | lower grade | lower grade | higher grade | higher grade |
| *RespTM* | 0.06368*** | 0.06707*** | −0.00886 | −0.00701 |
| | (0.01533) | (0.01534) | (0.01418) | (0.01424) |
| *RevAvg* | −0.26708*** | −0.26717*** | −0.28109*** | −0.27998*** |
| | (0.00676) | (0.00675) | (0.00803) | (0.00808) |
| *RevVar* | −0.02985*** | −0.03147*** | −0.04257*** | −0.04135*** |
| | (0.00823) | (0.00823) | (0.00885) | (0.00891) |
| *RespRatio* | 0.05776*** | 0.05771*** | 0.00446 | 0.00447 |
| | (0.01163) | (0.0116) | (0.00813) | (0.00816) |
| *LnRespInterval* | −0.00595* | −0.00571* | −0.00701* | −0.00712* |
| | (0.00283) | (0.00283) | (0.00287) | (0.00287) |
| *LnRespLen* | 0.02463** | 0.02410** | 0.00527 | 0.00491 |
| | (0.00871) | (0.00868) | (0.00860) | (0.00861) |
| *RespTM*RevAvg* | | −0.1893*** | | 0.04102 |
| | | (0.04380) | | (0.05025) |
| *RespTM*RevVar* | | −0.13584** | | 0.07392 |
| | | (0.05033) | | (0.05123) |
| Constant | 0.97157*** | 0.97445*** | 1.237*** | 1.232*** |
| | (0.05309) | (0.05302) | (0.05586) | (0.05597) |
| Observations | 2809 | 2809 | 2077 | 2077 |
| R-squared | 0.45928 | 0.46304 | 0.49214 | 0.49269 |
| Adj R-squared | 0.43807 | 0.44156 | 0.47099 | 0.47103 |

Standard errors in parentheses.
*p < 0.05, **p < 0.01, ***p < 0.001.

**Table 7**
Estimation results by quarter.

| *RatingGR* | model 7 | model 8 |
|---|---|---|
| | all sample | all sample |
| *RespTM* | 0.04127*** | 0.03533** |
| | (0.01227) | (0.0125) |
| *RevAvg* | −0.27440*** | −0.27343*** |
| | (0.00535) | (0.00535) |
| *RevVar* | −0.02818*** | −0.02829*** |
| | (0.00701) | (0.007) |
| *RespRatio* | 0.01599* | 0.01648* |
| | (0.00699) | (0.00698) |
| *LnRespInterval* | −0.00436* | −0.00451* |
| | (0.00188) | (0.00188) |
| *LnRespLen* | 0.01232* | 0.01321* |
| | (0.006) | (0.00599) |
| *RespTM*RevAvg* | | −0.153*** |
| | | (0.0345) |
| *RespTM*RevVar* | | −0.15144*** |
| | | (0.0456) |
| *RespTM*HotelStars* | | −0.04115* |
| | | (0.02005) |
| Constant | 1.076*** | 1.071*** |
| | (0.03842) | (0.03839) |
| Observations | 5236 | 5236 |
| R-squared | 0.43482 | 0.43773 |
| Adj R-squared | 0.37566 | 0.37848 |

Standard errors in parentheses.
*p < 0.05, **p < 0.01, ***p < 0.001.

**Table 8**
Estimation results by quarter with different hotel grades.

| *RatingGR* | model 9 | model 10 | model 11 | model 12 |
|---|---|---|---|---|
| | lower grade | lower grade | higher grade | higher grade |
| *RespTM* | 0.0483*** | 0.04756*** | −0.0107 | −0.011 |
| | (0.01433) | (0.01435) | (0.01732) | (0.01741) |
| *RevAvg* | −0.27775*** | −0.2768*** | −0.21597*** | −0.2155*** |
| | (0.00603) | (0.00603) | (0.01115) | (0.01115) |
| *RevVar* | −0.02698*** | −0.02751*** | −0.01164 | −0.01007 |
| | (0.00803) | (0.00802) | (0.01246) | (0.0125) |
| *RespRatio* | 0.02084* | 0.02172* | 0.00205 | 0.00144 |
| | (0.00876) | (0.00875) | (0.0071) | (0.00711) |
| *LnRespInterval* | −0.00457* | −0.00469* | −0.00142 | −0.00163 |
| | (0.00219) | (0.00219) | (0.00272) | (0.00272) |
| *LnRespLen* | 0.01405* | 0.01447* | 0.00601 | 0.00581 |
| | (0.00713) | (0.00711) | (0.00755) | (0.00755) |
| *RespTM*RevAvg* | | −0.15111*** | | −0.03275 |
| | | (0.03830) | | (0.10334) |
| *RespTM*RevVar* | | −0.1463** | | −0.13565 |
| | | (0.05139) | | (0.10611) |
| Constant | 1.059*** | 1.055*** | 0.91917*** | 0.91754*** |
| | (0.04457) | (0.04449) | (0.06671) | (0.06671) |
| Observations | 4149 | 4149 | 1087 | 1087 |
| R-squared | 0.43658 | 0.43906 | 0.43581 | 0.43718 |
| Adj R-squared | 0.37529 | 0.3777 | 0.38234 | 0.38261 |

Standard errors in parentheses.
*p < 0.05, **p < 0.01, ***p < 0.001.

management response, but in this study, we investigate the moderating effect of hotel grade on management response and re-estimate the overall empirical models by using different classes of hotels. Our results show that the hotel grade negatively moderates the effect of personalized management response on rating increase. Furthermore, the overall empirical models in the sample of lower-grade is also stable and consistent with the main results, but the sample of higher-grade fail the test. That is, our findings act a stronger role in the lower-grade hotel (versus higher-grade hotel). Specifically, we also attempt to analyze the practical significance of such effects in combination with the actual situation of the hotels. The summary in Table 10 reveals the characteristics of management responses of hotels with a different grade. The average of online rating increases over hotel grades. Although the percentage of responded reviews in 1-star hotels is the highest among all hotel grades, their lowest topic matching level of management responses (Average of RespTM %) implies the inferior responses strategy. It has been noted that the topic matching level of management response in hotels under 3.5 stars is relatively lower, and there is ample space for improvement in online rating. In light of our findings, lower-grade hotels should pay more attention to the topic matching of management responses in order to improve the online rating.

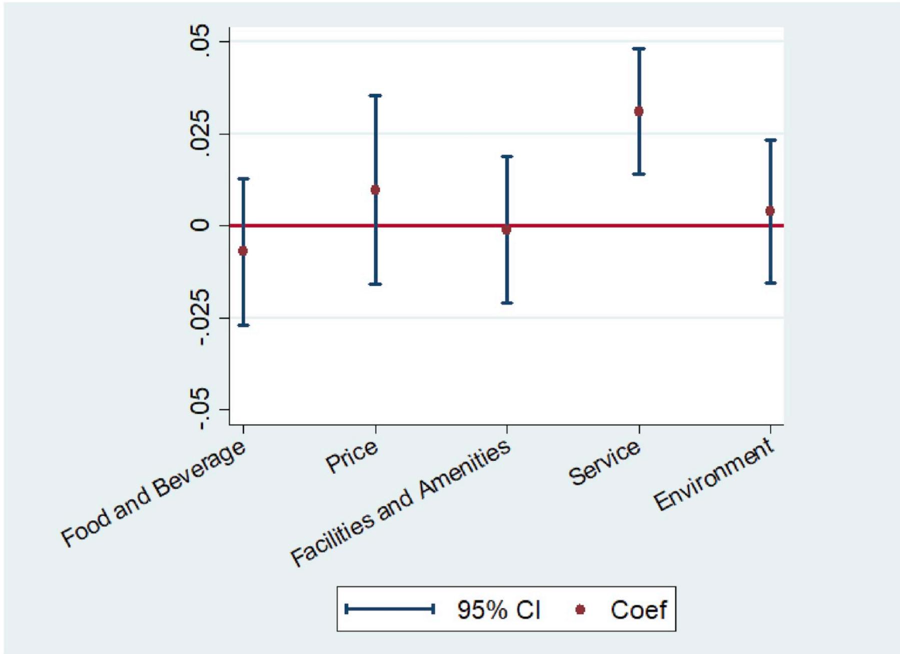


**Fig. 7.** Effects of five topic types.

### *5.2. Theoretical implications*

This study contributes to theoretical implications on the strategies of management response in a few ways. First, it complements the previous literature that has extensively focused on the effects of management response based on consumer reviews (Lee & Cranage, 2014; Li et al., 2017; Wei et al., 2013; Xie et al., 2017) by providing a new perspective of topic matching. In particular, Xie et al. (2017) defined the repetition of topics between responses and reviews and implied that reacting with fresh topics prior to repeating the service failure descriptions in consumer's complaints. They highly focused on the different and constructive information topics that may divert consumer's attention to other positive aspects of products or services rather than unsatisfactory experiences and complaints. Nevertheless, some specific content in the new topics of responses that can make consumers perceived cognitive fit needs further confirmation. On this basis, the personalized management response in this study further highlighted the topic-matched content in management responses and mainly aimed to come up with specific explanations, solutions and other relevant content around the topic of customer complaints. We applied the machine-learning approach to recognize the response that is relevant to the same topic of review in an automatic and rigorous way, and present the topic matching degree to measure the content relationship between them. Specifically, this study first introduces the idea of topic matching of

**Table 9**
Estimation results by month with different topics.

| *RatingGR* | model 13 | model 14 | model 15 | model 16 | model 17 |
|---|---|---|---|---|---|
| | Topic of Food & Beverage | Topic of Price | Topic of Facilities and Amenities | Topic of Service | Topic of Environment |
| *RespTM* | −0.00727 | 0.00916 | −0.00053 | 0.0295*** | 0.00375 |
| | (0.01009) | (0.01303) | (0.01012) | (0.00873) | (0.0099) |
| *RevAvg* | 0.0183 | 0.0233* | 0.03*** | 0.024*** | 0.0121 |
| | (0.01303) | (0.01229) | (0.00779) | (0.00811) | (0.01086) |
| *RevVar* | −0.223*** | −0.261*** | −0.27*** | −0.274*** | −0.261*** |
| | (0.00897) | (0.00863) | (0.00532) | (0.00552) | (0.00761) |
| *RespRatio* | −0.0269*** | −0.037*** | −0.0345*** | −0.0393*** | −0.0437*** |
| | (0.01039) | (0.01067) | (0.00634) | (0.00654) | (0.00872) |
| *LnRespInterval* | −0.00022 | −0.00057*** | −0.00037*** | −0.00043*** | −0.00005 |
| | (0.00017) | (0.00018) | (0.0001) | (0.0001) | (0.00015) |
| *LnRespLen* | 0.00056*** | 0.00033 | 0.00038*** | 0.00052*** | 0.00031* |
| | (0.00019) | (0.0002) | (0.00013) | (0.00013) | (0.00017) |
| *RespTM*RevAvg* | | | | | |
| *RespTM*RevVar* | | | | | |
| *RespTM*HotelStars* | | | | | |
| Constant | 0.928*** | 1.103*** | 1.126*** | 1.129*** | 1.117*** |
| | (0.04823) | (0.047) | (0.02947) | (0.0302) | (0.04075) |
| Observations | 1821 | 1829 | 4608 | 4466 | 2440 |
| R-squared | 0.384 | 0.453 | 0.465 | 0.47 | 0.424 |
| Adj R-squared | 0.318 | 0.393 | 0.442 | 0.447 | 0.378 |

Standard errors in parentheses $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

**Table 10**
Distribution of management responses by hotel grade.

| Hotel Grade | No. of Reviews | No. of Responses | Reviews Responded (%) | Average of Rating | Average of RespTM (%) |
|---|---|---|---|---|---|
| 1–1.5 Stars | 316 | 217 | 68.67 | 3.23 | 36.13 |
| 2–2.5 Stars | 42,615 | 23,510 | 55.17 | 3.7 | 40.9 |
| 3–3.5 Stars | 91,074 | 59,017 | 64.8 | 4.08 | 40.83 |
| 4–4.5 Stars | 83,725 | 49,483 | 59.1 | 4.3 | 39.87 |
| 5 Stars | 3549 | 1820 | 51.28 | 4.53 | 44.32 |

Note: The summary statistics are based upon the sample crawled on November 15, 2016.

management response in the existing management-response literature.

Second, given that some studies only focus on negative reviews (Gu & Ye, 2014; Lee & Cranage, 2014; Sparks & Bradley, 2017), personalized management responses in this study are appropriate for all the sentiment polarity of reviews. Different from prior studies specialized in management response to the dissatisfied reviews; we also consider effective management response to positive reviews. By examining the topic-matching degree between management response and consumer review, this study contributes to the literature with a more comprehensive understanding of how management response influences the consumer's evaluation of different ratings of reviews. Therefore, we highlight the personalized response as a comprehensive strategy for hotel business for customer relationship management.

Finally, given that prior studies utilize survey and experimental data to seek the effects of management response (e.g., Lee & Cranage, 2014; Mauri & Minazzi, 2013), this study presents a comprehensive analysis of the influence of personalized management response using a data analytics approach through a large-scale panel data based on revealed behavior (Yang, Mao, & Tang, 2018). Even though some scholars used the similar dataset to explore the strategies of management response, we specifically combine the generated management response and generated consumer review to measure the influence of personalized management response, and empirically examine how management responses can significantly influence the hotel rating increase and whether its effects depend on hotel grades. In this process, we demonstrated the usefulness of the machine-learning technology in developing proper strategies of management responses.

### 5.3. Practical implications

This study provides practical implications for tourism management. First, our findings show that the topic matching of management response has a positive impact of on rating increase. On this basis, it is critical for hotel managers to adopt a useful and personalized strategy to response current consumers who post online reviews and to attract more subsequent customers. Compare to the genetic response similar to the over-standardized template; managers should seriously understand which topic the reviews mentioned, and respond relevant topic content to the consumers. A number of prior studies stated that managers need to respond to relevant content mentioned in the consumer review, but they have not explicitly pointed out how to respond. The result indicates that service operators should take their resource allocation strategy for personalized management responses and give priority to match the specific topic in consumer reviews. Our discussion with the topic matching of management response is clearer and more detailed for practical application in the tourism industry.

Second, we further investigate the effectiveness of hotel grades, and the results indicate that personalized management response has a stronger impact on rating increase in the lower-grade hotels. In addition, it can be seen from the descriptive statistics that the level of personalization of management responses is relatively lower in lower-end hotels. Therefore, in the case where the hotel rating has ample space for improvement, managers in economy hotels should pay more attention to apply these research results to increase the online rating.

Third, we recognized several topics revealed in online reviews. More importantly, we further found that the effect of topic matching related to the service topic is most substantial among the five topics. We highly recommend the hoteliers to closely monitor the performance of their properties across these topics and develop specific strategies to conduct online reputation management under these relevant topics, especially for direct interactions with customers such as front-desk service, which represents the very first opportunity to shorten the social distance from customers. If possible, some 'studies' are necessary to learn from competitors and 'best' practitioners in this regard. Hotels should also train their employees on how to appropriately respond to the customer feedback on different topics, irrespectively online or offline.

Fourth, after unveiling the impact of topic-matched responses on hotel reputation, an intelligent assistance system can be developed for hotel management responses. The system automatically recognizes the topics covered in the consumer reviews and highlights them to alert the review repliers. After the replier edited the response, the system is able to display topic matching score to help them improve the response quality. All consumer review topics and management response quality are recorded in a massive database and serve as a business intelligence analysis platform to assistant hotel managers to monitor response quality.

### 5.4. Limitation and future research

This study has several limitations that offer possible directions for future research. First, although this research controls the heterogeneity of hotel in the empiric model, some other factors that may influence the management responses are not included due to data unavailability. For example, service operators' career positions, capability, and orientation toward online reviews and social media strategy, as well as an internal corporate culture on internet-based customer review response, could all influence the practices and effectiveness of management responses. Also, the diversity of consumers' personality, prior online review usage experience, personal preferences, and cultural background, etc. may also influence the perception of management response and their individual decision-making, which in turn affects the hotel rating changes. These factors could be included in future research when data is made available. Additionally, although we extracted the core topic from consumer reviews using the SVM model, we disregarded other branch topics included in an online review. Notably, the multi-topic matching of management responses represents a promising research field for future efforts.

Finally, our data collected from a single US state from a single review website (TripAdvisor). The availability of the large-scale data enables a comprehensive perspective of the interrelationships among personalized management responses, consumer reviews and hotel rating increase, but findings from one individual city may not be generalizable to other hotel markets. Therefore, future research could use data from other cities or regions in other countries or cultures to empirically test the hypotheses and improve the generalizability of the results.

## Author contribution

Xiaowei Zhang, Shuchen Qiao, Yang Yang and Ziqiong Zhang contributed equally to this research paper, including conceptualization, validation, data processing and analysis, writing-original draft preparation, writing-review and editing, etc.

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## Appendix A

List of top 200 feature words.

| Topic | Feature Words (Top 200 words) |
|---|---|
| Food and Beverage (41 words) | food, breakfast, buffet, delicious, cheese, fruit, meal, tasty, dinner, dine, cookie, egg, lunch, bacon, steak, bean, water, milk, deal, drink, beverage, folk, cook, turkey, chicken, burger, brunch, bar, alcohol, kitchen, wine, pizza, freshest, gobble, potato, bake, cafe, tea, tomato, biscuit, eat. |
| Price (23 words) | charge, per, price, fee, pay, cost, rate, expense, tax, pricey, discount, cheaper, buy, free, worth, sticker, cash, USD, bill, cheap, dollar, bonus, $. |
| Facilities and Amenities (53 words) | room, park, clean, bed, garage, bathroom, facility, lobby, spacious, internet, floor, small, pillow, connect, step, wifi, shower, spa, cabana, wireless, temperature, modern, rooftop, microwave, door, ground, toilet, guestroom, soft, downstairs, sleep, gate, fence, cup, Hotwire, chair, hall, warm, texture, soup, loft, cooler, bath, clock, grate, wooden, passageway, window, ballroom, restroom, armchair, bathtub, mirror. |
| Service (36 words) | staff, friendly, comfort, front desk, courteous, professional, check, finest, smile, team, waiter, welcome, employee, bellman, greet, kind, housekeeper, order, bellmen, waitress, person, assist, response, debit, register, driver, call, credit, officer, manner, honest, cleaner, wakeup, leader, guardsmen, manual. |
| Environment (47 words) | locate, walk, riverwalk, river, shop, distance, close, downtown, resorts, area, vehicle, restaurant, quiet, golf, nearby, mall, taxi, surround, transport, freeway, market, hospital, mile, noise, railway, uber, museum, Starbucks, traffic, bus, airport, address, highway, near, instance, school, road, marketplace, store, countryside, lake, church, landscape, town, hill, train, sunlight. |

## Appendix B

Examples of Training Data.

| Topic | Texts |
|---|---|
| Food and Beverage | 1. The morning breakfast cook in the restaurant was great. He does do an incredible job with the breakfast buffet and I enjoyed the eggs!<br>2. The best thing was the breakfast buffet … yummy my son who is a picky eater enjoyed it.<br>3. The coffee and tea provided in the room was not very good. The earl grey was bitter as was the coffee. |
| Price | 1. The price was great.<br>2. They charge for self-parking in a covered garage ($16/day) or valet ($27/day).<br>3. The valet option was priced at $29 a night plus tax, but worth it when there is a large event going on in the city. |
| Facilities and Amenities | 1. The room was not cleaned every day during my stay.<br>2. The toilet was leaking.<br>3. We are sad to realize that the hotel is in the process of upgrading the wireless internet access and might be offering Wi-Fi in all guestrooms by the second quarter of 2012. |
| Service | 1. The staff in the hotel was friendly.<br>2. Staff was nice. But a desk person told us we could easily walk to the restaurant, but it turned out to be about 2 miles!<br>3. Staff was very friendly, courteous and willing to help. Concierge service is exceptional. |
| Environment | 1. I enjoyed the ideal location of the resort.<br>2. The hotel is located on the river walk, about a 10-min walk away from the “touristy” part.<br>3. The hotel is located “on the river walk” but further away from most of the restaurants, etc. |

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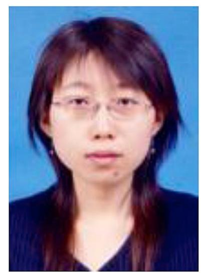

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