**Managerial Responses to Online Reviews: A Text Analytics Approach**

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## Abstract

The study tests the effects of online managerial responses and returning customers' future satisfaction (measured as review ratings) by performing social media text analytics on a hotel sample. Essentially, this article provides insight into meaningful differences in future ratings between responding and non-responding hotels, as well as differences in response styles between ratings improvement and non-improvement. The results indicate that: 1) subsequent ratings are higher if customers receive responses to their previous online reviews; 2) increase in ratings is more significant among low-satisfaction customers, and a decrease in ratings is mitigated if responses are provided; 3) responding to loyal customers – those who have visited and rated the same hotel more than three times – has a limited impact on ratings; 4) responses are longer and sentiment is slightly lower in scenarios where subsequent ratings are improved, but there is no significant difference in the effect of response speed between the two groups; 5) changes in ratings also affect styles of responding to current reviews – if customer satisfaction has improved, response length tends to be shorter and sentiment level tends to be higher. The findings offer both theoretical and managerial implications by demonstrating the utility of social media text analytics.

**Keywords**: text analytics; business performance; online reviews; online ratings; hotel industry

# 1 Introduction

In today's data-rich competitive environment, corporate executives face a serious challenge of how best to assemble and utilise a vast amount of user-generated data to not only position their products or services, but also segment their markets (Sorescu, 2017). For example, if a customer has a positive experience staying at a hotel or a dreadful dining experience, instead of complaining to the customer service representative at the hotel/restaurant, a customer will write a review online, or share their experience through one of the many social media platforms. The praises or complaints about a product/service posted on a social media platform are public, and can be seen and shared by millions of people around the world. Thus, capturing and utilising user-generated data for analysis can help firms from various industries out-perform their competitors (Marshall, Mueck and Shockley, 2015; Sorescu, 2017). However, it is unclear how a firm can utilise social media generated vast amount of data to improve customers' attitudes toward its product/service and customers' overall perception of the organisation to enhance the firm's performance (Hofacker, Malthouse and Sultan, 2016; Johnson, Friend and Lee, 2017).

In the past, many firms sustained a competitive edge primarily by responding to customers' complaints and any comments directed at them (see Mayer-Schönberger and Cukier, 2013; McAfee and Brynjolfsson, 2012). Previously, this was an effective response, and it enabled organisations to survive and thrive. However, in the technological era and due to the proliferation of social media sites such as Twitter, Facebook and TripAdvisor, organisations can no longer rely on their websites alone to better serve and meet their customers' needs (see Sorescu, 2017; Constantiou and Kallinikos, 2015). Customers now expect organisations to respond to the comments and complaints posted on all social media platforms (see Johnson, Friend and Lee, 2017; Kuksov and Xie 2010, Li, Hitt and Zhang, 2011). Indeed, it has become a strategic imperative for organisations to shift toward more nimble and flat hierarchies that enable them to proactively respond to customers' complaints and concerns irrespective of whether they were made directly to them or posted on social media sites. In the past, firms were unable to tap into and leverage the significant amount of unstructured data available on web-based platforms. Recent progress made in this area, however, enables firms to capture value from the vast amount of available, unstructured data (George et al., 2014). Nevertheless, our present understanding of how firms can best capture and respond to the vast amount of available data remains relatively underdeveloped. Recent research suggests that technologies and social media text analytics can help firms harness the significant potential of both structured and unstructured data (Chen et al., 2012, Khan and Vorely, 2017).

For example, within the hospitality sector, the public nature of online reviews for hotels means that such reviews play an important role in many potential consumers' decisions and thus present significant business value (cf. Xie, Zhang and Zhang, 2014). While favourable reviews can attract more customers and increase demand, unfavourable reviews can have a significant negative impact on firms' online reputation (Lappas, Sabnis and Valkanas, 2016; Wang and Chaudhry, 2017). Regarding the economic impact of online reviews, many firms respond to individual reviews as an intervention strategy to protect and/or enhance their online reputation and improve hotels' financial performance (Xie et al., 2014). Indeed, a firm's ability to identify and respond to such comments can actually help it develop a sustainable competitive advantage.

Although there is a consensus within the literature regarding the strong positive relationship between management responses and a firm's online reputation and performance (Sparks, So and Bradley, 2016; Proserpio and Zervas, 2017; Wang and Chaudhry, 2018), the best way to respond to different reviews has yet to be identified. Specifically, the effects of different responding styles, in terms of response speed, length and sentiment, remain unclear. Furthermore, the majority of existing studies examine the impact of management responses for online reviews posted by all customers (Xie et al., 2014; Proserpio and Zervas 2017; Wang and Chaudhry 2017). However, if customers only consume service once, whether or not a manager responds to their reviews may have a little impact on their future ratings. Wang and Chaudhry (2018) have further noted that a lack of repeat reviewers in their sample limited their ability to study user heterogeneity. Moreover, in current literature, there is limited evidence (e.g., Gu and Ye, 2014) regarding whether online management responses to returning customers' postings can improve future customer ratings. Therefore, we focus only on returning customers to examine the relationship between management responses and customers' ratings.

In this study, we seek to fill these voids by examining the effect of managerial online responses on returning customers' behaviour (e.g., future review provision and review ratings); In particular, we attempt to examine the effectiveness of different response styles. The issue of favourable reviews and high ratings is particularly important given that past studies have demonstrated that consumers do actually prefer products with favourable reviews (Kuksov and Xie, 2010, Li, Hitt and Zhang, 2011). Furthermore, returning customers can provide a unique testimony about the firms' offerings and their insights can determine whether or not firms are attentive to both disgruntled and satisfied customers. To explore these complex relationships, we tested the effects of managerial online responses on returning customers' future satisfaction (review ratings) using 40,604 online reviews of 770 hotels from 13,610 distinct reviewers and 23,106 management responses. Our main argument is that responding to returning customers' online reviews can be an effective mechanism for firms to develop and enrich their knowledge and improve competitiveness in terms of online reputation.

The study contributes to the extant literature on business strategy, marketing and hospitality management in several ways. First, unlike other studies, we explore whether there is any meaningful difference in the future ratings of responding and non-responding hotels, as well as whether there is any meaningful difference in response styles between rating improvement and non-improvement. Thus, we shed light on whether utilising social media data improves returning customers' ratings and satisfaction. In doing so, we deepen our understanding of the role of social media in strategic formulation (see Wamba et al., 2017). In addition, one perennial, yet underexplored, issue is how firms can better utilise user-generated content in the age of digitisation. This study extends the current research on the knowledge-based view of a firm (Grant, 1996; Nonaka, 1994) by examining how firms harness social media data to develop new ways of responding to customers. The present study also expands our understanding of the customer-management relationship (Gu and Ye, 2014; Xie et al., 2014; Wei, Miao and Huang, 2013) by exploring firms' active management of online customer reviews; it moreover provides deeper insight into how to improve future ratings via response style. By drawing on social media and online review literature (Liu, Feng and Liao, 2017), we develop a theoretical position on how customers' ratings can differ significantly based on whether or not hotels did or did not respond to previous reviews. On this basis, we utilise social media text analysis to enrich our understanding of how managerial responses can be shaped to improve customers' perception of firms.

The remainder of this article proceeds as follows: In the next section, we review the relevant literature. Subsequently, the adopted approaches for data collection and text analytics are explained. We then present our findings and establish the study's contributions to extant theory and practice, and provide directions for further research.

## 2 Overview of Relevant Literature

In this study, we explore how to properly respond to online reviews. The extant literature suggests that online reviews can help customers learn about a product or service, thereby reducing the information asymmetry between the two parties – i.e. the service provider and the user (Chen and Xie, 2005; Liu, Feng and Liao, 2017). Recently, the notion of continuously scanning customers' postings and online reviews and delivering responses has become a strategic component through which firms can capture value and develop new knowledge (e.g., Liu, Schuckert and Law, 2018; Tseng and Wu, 2014; Xiang, Schwartz, Gerdes and Uysal, 2015). The advent of the present data-rich environment requires firms to mobilise and harness both structured and unstructured data sources to generate new knowledge and thus, optimise operations (Tian, 2017; Khan and Vorely, 2017). For instance, through a data mining approach, Guo, Barnes and Jia (2017) have extracted key dimensions/factors that influence consumer satisfaction from online hotel reviews and identified differences according to demographic segments.

As the number of customers who write online reviews continues to grow (Schuckert, Liu and Law, 2015), it is clear that responding to online reviews can potentially be an important mechanism for developing a more adaptive organisation. Some of the unique features of customers' online reviews are that they tend to be up-to-date and widely available to potential and current customers of a business (Schuckert et al., 2015). Prior research has indicated that management responses can increase the future ratings of low-satisfaction customers, but decrease their satisfaction if they do not receive a response (Gu and Ye, 2014; Proserpio and Zervas, 2017). In today's hyper competitive environment, firms have only a small window of opportunity in which to respond to customers' complaints and comments before the situation has the opportunity to escalate into a full-blown organisational crisis.

The notion of reconfiguring firms' activities to respond to new threats or take advantage of market opportunities is anchored in the dynamic capabilities perspective (e.g., Teece, Pisano and Shuen, 1997; Pisano, 2017). Dynamic capabilities refer to a "firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece, Pisano and Shuen, 1997, p. 516). Prior research into dynamic capabilities and agility has indicated that firms with strong dynamic capabilities are in a better position due to their unique abilities to identify and respond to new market information (see Teece, Peteraf and Leih, 2016; Junni et al., 2015; Weber and Tarba, 2014).

Consistent with this perspective, some have suggested that this era of big data requires organisations to become more agile and proactive in identifying threats and opportunities and take advantage of any found opportunities using sources such as customers' reviews and online blogs to innovate and improve competitiveness (e.g., George et al., 2014; Teece, Peteraf and Leih, 2016; Sheng et al., 2017). After sensing a change in consumers' behaviour or new opportunities stemming from online review data analysis (Sheng et al., 2017, 2018), firms may not only have to redesign product and service offerings, but also change their business model (see Lavie, 2006; Teece, 2010). By harnessing user-generated data, firms can innovate and respond to changing customers' demands and environmental changes in a timely manner (Wessel, 2016). Indeed, firm capabilities echo the abilities to deploy resources (Lin et al., 2013) to become innovative and respond to changing business environment are essential (Johnson, Friend and Lee, 2017).

An example of a dynamic capability is the ability to sense and scan the business environment, and then mobilise the firm's processes and resources to respond to or exploit market opportunities (Teece, 2007). As Johnson et al. (2017, p. 644) have observed, regarding new product development and innovation, "big data capabilities bring improvements to the processes built around discovering market opportunities and offering customers high value products". Indeed, "organisations using big data and analytics within their innovation processes are 36% more likely to beat their competitors in terms of revenue growth and operating efficiency" (Marshall, Mueck and Shockley, 2015, p. 32). Organisational learning occurs when employees seek, gain and utilise internal and external information and deduce lessons or insights that enhance a firm's processes, responses, routines and procedures (Levitt and March, 1988). Overtime, such knowledge equips the organisation to make well-informed decisions and chart a better course of action.

The knowledge-based view (KBV) asserts that knowledge is a key resource for firms seeking to develop new sources of competitive advantage (Grant, 1996; Nonaka, 1994). A firm's KBV (Spender 1996) suggests that a firm's ability to outperform rivals is predicated on its ability to develop and utilise valuable knowledge through learning. The insights gained from learning can be utilised across the functional unit of the organisation to ultimately improve performance (Bogner and Bansal, 2007). Knowledge refers to "any information, belief, or skill that the organisation can apply to its activities" (Anand, Glick and Manz, 2002, p. 88). Through big data analytics, firms are able to mobilise new customer data and develop vast amounts of new knowledge (Chen et al., 2012), which can be used to form the basis of a firm's product innovation or customer responses (Akter et al., 2016). Recent advances in this area suggest, that by harnessing big data, organisations are able to develop a reservoir of knowledge to innovate and effectively compete (Johnson, Friend and Lee, 2017; Pauleen and Wang, 2017; Tian, 2017). Indeed, knowledge accumulation and utilisation remain a key component in firms' ability to innovate and develop new service delivery mechanisms (Grant, 1996). Harnessing knowledge through textual analysis of online reviews is vital for the highly dynamic and competitive hotel industry as through this hotel chains can improve customers' satisfaction which may result in better financial performance (Liu et al., 2018; Xie et al., 2014). Yet, there is limited examination of how firms could harness the potential knowledge generated through online reviews and improves returning and potential customers' satisfactions and service quality.

By sensing and seizing market opportunities, organisations would be in a position "to build strong market orientation cultures in order to be successful in hostile market and industry environments" (Atuahene-Gima, 1995, p. 286). By utilising knowledge from social media data (Sheng et al., 2017), firms are able to develop specific knowledge that is difficult for rivals to imitate or utilise to innovate (Argote and Ingram, 2000). This view is in accordance with existing studies that have suggested that organisations endowed with superior capabilities in capturing big data for both the creation and transfer of knowledge are more likely to outperform their rivals (Amankwah-Amoah, 2015; George et al., 2014; Wamba et al., 2017). Due to the potential benefits arising from applying big-data-oriented technologies (such as text analytics), firms from different industrial settings are becoming increasingly interested in utilising big data related resources to develop a competitive advantage (Davenport, 2013; George et al., 2014).

After determining how to best utilise social media data, organisations are required to respond to both non-returning and returning customers. In spite of these potential benefits, previous research offers limited insights into how a firm's response style (e.g. responding speed, length and sentiment) impacts future ratings. It is also unclear whether responding to customers actually delivers superior benefits. Returning customers are particularly important given their ability to provide rich insights and influence current and future customers. Thus, this study seeks to address the aforementioned gaps in the literature by utilising big data text analytics on online reviews in a diverse set of hotel chains.

# 3 Research Methods

## 3.1 Data

To analyse response styles and their impact on customer ratings, we collected reviews and responses from a leading travel platform. The sample consists of hotels in London. This city was chosen because it is seen as a top international destination and a competitive market with a substantial number of hotels. By applying a web crawler, we downloaded the entire history of reviews and responses of London hotels found on the site. Information extracted includes hotels' names, reviewers' names, review dates, numeric rating, review text, response dates and response text. The raw dataset comprises 1,063 hotels and covers a 15-year period from December 2001 to February 2016[1].

Based on our identification strategy, we focused on repeat reviewers (returning customers) who provided multiple reviews of the same hotel. Thus, the initial sample comprises 41,396 reviews. To further narrow the data set, we removed duplicates in terms of users and hotels. We also excluded reviews that are written by the same user for the same hotel on the same day, because we are unable to determine the sequential order of these reviews. Furthermore, we removed observations with non-English responses because we intend to perform text mining on the response text and need to maintain language consistency. Finally, we ensured that each reviewer has at least two reviews of the same hotel. The final sample contains 40,604 reviews of 770 hotels from 13,610 distinct reviewers and 23,106 management responses attached to these reviews, covering a period from July 2003 to February 2016.

[1] Data was collected in March 2016.

### 3.2 Text Analysis

We conducted a text analysis to quantify the unstructured response text. First, we measured response length by extracting the word count of each management response. Using non-letter characters as splitting points, the text is tokenised into a sequence of tokens. Thus, each token is a single word; By calculating the number of words, we obtained the length of each management response.

In addition, a sentiment analysis was performed to detect the sentimental orientation of managerial responses. With the aid of computational techniques, we were able to uncover and classify semantic and emotional information hidden within the textual documents (Pang and Lee, 2004, 2008). We employed a linear Support Vector Machine (SVMs), which is the simplest usable algorithm that produces the high performance in sentiment analysis (Pang, Lee and Vaithyanathan, 2002). To construct a classification model, we first created a training dataset that contains 350 examples of management responses, randomly selected from our sample. We manually labelled each document in the training set based on the positivity and negativity revealed within the response's content and cross-checked the manual classification results with an open-source sentiment analysis tool, SentiStrength[2]. Subsequently, the training set was used to tune the classifier and a ten-fold cross-validation was conducted to assess the model's performance. Overall, the SVMs classifier exhibits an accuracy of 92.57% and F-measure of 95.7%[3]. We then applied the classifier to all management responses in our sample. Each response document is classified as positive or negative with a confidence score ranging from 0 to 1. A positive class score is extracted as a measure of sentiment polarity. A higher score (closer to one) indicates a more positive sentiment in the response content, while

[2] SentiStrength (http://sentistrength.wlv.ac.uk/) is an open source program for automatic sentiment analysis.
[3] F-measure is the harmonic mean of precision and recall, which is calculated as F = 2*Precision*Recall / (Precision+Recall). Precision is the positive predictive value and recall is the true positive rate (see Netzer et al., 2012).

a lower score (nearer to zero) demonstrates a negative sentimental orientation. In total, the prediction yields 21,745 positive responses (sentiment score ≥ 0.5) and 1,361 negative responses (sentiment score < 0.5), resulting in an average sentiment level of 0.6974.

### 3.3 Empirical Approach

We conducted a statistical analysis (two-sample t-tests) to determine: 1) if future rating of a customer differs depending on whether his/her previous review received a response; 2) if the response style to the previous reviews (i.e. speed, length and sentiment) affects increased or decreased future ratings; and 3) if the responding style differs depending on whether a customer gives a higher or lower rating than previously. Table 1 lists and defines the variables, as well as their summary statistics.

**Table 1. List of Variables and Summary Statistics**

| Variables | Description | N | M | SD | p50 | Min | Max |
|---|---|---|---|---|---|---|---|
| $Rating_{ihv}$ | Numerical rating of customer i's $v^{th}$ stay with hotel h (on a scale of 1-5) | 40,604 | 4.3215 | 0 .9304 | 5 | 1 | 5 |
| $RatingChange_{ihv}$ | The difference between the numerical ratings of customer i's $v^{th}$ and v-$1^{th}$ stay with hotel h | 21,951 | -0.0183 | 1.0056 | 0 | -4 | 4 |
| $Increase_{ihv}$ | Dummy variable, taking value of 1 if $RatingChange_{ihv}$ is greater than 0; taking value of 0 otherwise | 21,951 | 0.7930 | 0.4051 | 1 | 0 | 1 |
| $Response_{ihv-1}$ | Dummy variable, taking value of 1 if a response is provided to the review of customer i's v-$1^{th}$ stay with hotel h; taking value of 0 otherwise | 21,951 | 0.5425 | 0.4982 | 1 | 0 | 1 |
| $ResponseDays_{ihv-1}$ | The number of days between a management response and the associated review of customer i's v-$1^{th}$ stay with hotel h | 11,908 | 12.1544 | 65.6196 | 4 | 0 | 1,773 |
| $ResponseLength_{ihv-1}$ | The number of words in a management response to the review of customer i's v-$1^{th}$ stay with hotel h | 11,908 | 85.3627 | 47.0331 | 75 | 5 | 777 |
| $ResponseSentiment_{ihv-1}$ | Sentiment score of a management response to the review of customer i's v-$1^{th}$ stay with hotel h | 11,908 | 0 .6975 | 0.1087 | 0.7171 | 0.1866 | 0.9374 |

Note: The actual number of stays of customer i with hotel h are unobservable to us. We use the $n^{th}$ review of customer i on hotel h as a proxy.

## 4 Results

### 4.1 Descriptive Statistics

Table 2 summarises the distribution of reviews and ratings, hotels, reviewers and management responses in our sample. As shown in Panel A, there are a total of 770 hotels, of which 518 hotels (67.27%) responded to a review at least once in the sample period. The overall response rate is 56.91%. It can be seen that 4-star (91.84%) and 5-star hotels (89.42%) are the most proactive in providing responses to online customer reviews, with a response rate of 66.34% and 62.77%, respectively. Regarding rating distribution in the sample (see Panel B), customer satisfaction is predominantly positive with high ratings (i.e., 4-score and 5-score ratings) accounting for 84.64% of the reviews given by 87.37% of reviewers. Response rates are very similar (ranging from 51.61% to 61.87%) across different review rating levels. Most subsequent ratings remain unchanged (59%), and the probability of improvement in subsequent ratings varies with earlier review ratings. Low-satisfaction customers are more likely to increase ratings in later reviews, while high-satisfaction customers tend to rate at a similar level.

**Table 2. Distribution of Hotels, Reviewers, Reviews and Responses**

| Panel A: Distribution of hotel, customer review and management response | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Hotel Class | Number of Hotels | Percent 1 | Number of Responding Hotels | Percent 2 | Number of Reviews | Percent 3 | Number of Response | Percent 4 |
| 5 | 104 | 13.51% | 93 | 89.42% | 8,295 | 20.43% | 5,207 | 62.77% |
| 4-4.5 | 245 | 31.82% | 225 | 91.84% | 21,042 | 51.82% | 13,960 | 66.34% |
| 3-3.5 | 296 | 38.44% | 167 | 56.42% | 9,746 | 24.00% | 3,491 | 35.82% |
| 2-2.5 | 88 | 11.43% | 24 | 27.27% | 1,120 | 2.76% | 396 | 35.36% |
| 1-1.5 | 6 | 0.78% | 2 | 33.33% | 100 | 0.25% | 10 | 10.00% |
| 0 | 31 | 4.03% | 7 | 22.58% | 301 | 0.74% | 42 | 13.95% |
| Total | 770 | 100% | 518 | 67.27% | 40,604 | 100% | 23,106 | 56.91% |
| Panel B: Distribution of reviewer and rating | | | | | | | | |
| Rating | Number of | Number of | Percent 6 | Number of | Percent 7 | | Subsequent Rating | |

| | Reviews | Responses | | Reviewers | | Increased | Unchanged | Decreased |
|---|---|---|---|---|---|---|---|---|
| 5 | 22,324 | 13,365 | 59.87% | 7,757 | 56.99% | 0 | 9,084 (75%) | 3,045 (25%) |
| 4 | 12,043 | 6,319 | 52.47% | 4,134 | 30.37% | 2,402 (36%) | 3,103 (46%) | 1,170 (18%) |
| 3 | 4,042 | 2,150 | 53.19% | 1,193 | 8.77% | 1,237 (60%) | 567 (27%) | 272 (13%) |
| 2 | 1,356 | 839 | 61.87% | 317 | 2.33% | 520 (79%) | 84 (13%) | 56 (8%) |
| 1 | 839 | 433 | 51.61% | 209 | 1.54% | 317 (77%) | 94 (23%) | 0 |
| Total | 40,604 | 23,106 | 56.91% | 13,610 | 100% | 4,476 (20%) | 12,932 (59%) | 4,543 (21%) |

Note: Panel A summaries the distribution of hotels, customer reviews and management responses across different star classes. In Panel A – percent 1 is given by the number of hotels in a star class divided by total number of hotels; percent 2 is the proportion of responding hotels in each star class; percent 3 is given by the number of reviews in each star class divided by total number of reviews; percent 4 is the proportion of reviews with management response provided. Panel B describes distribution of reviewers and ratings. In Panel B – percent 6 is the proportion of reviews with management response provided; number of reviewers are based on each distinct reviewer's first rating in the sample; percent 7 is given by the number of reviewers at each rating level divided by total number of distinct reviewers; the last three columns show the number of subsequent reviews with higher, equal, or lower ratings compared to previous ratings on the same hotel.

### 4.2 Impact of Providing Responses

We first performed a two-sample t-test to determine whether customers' future ratings differed depending on whether they received a management response to their previous reviews. The results in Panel A of Table 3 indicates that there is significant difference in subsequent ratings of reviewers whose previous reviews received responses from the service provider (M = 4.3896) compared to those who did not receive a management response (M = 4.2449). Overall, changes in ratings (i.e., the difference between current rating and previous rating) tend to be positive (M = 0.0136) when management responses are provided; While a decrease in subsequent ratings is observed when management did not respond to a previous review (M = -0.0562).

We therefore examined whether a significant difference exists in ratings between responding and non-responding hotels for low- or high-satisfaction customers (see Panel B of Table 3). For customers who did not give a hotel a "full score" after their last stay ($Rating_{ihv-1}$ below 5), it can be seen that their subsequent ratings are potentially higher (mean of $RatingChange_{ihv}$ is positive in all situations). Such an increase in subsequent ratings is more significant if their initial review received a management response. Particularly for unsatisfied customers ($Rating_{ihv-1}$ is 1 and 2), the difference in ratings between those who received a response and those who did not is considerable. Considering low satisfaction (a 1-score rating), on average, subsequent ratings increased by 2.64 in cases where the review received a response; This is 0.97 higher than the ratings improvement observed without management responses. Analogously, we find that high satisfaction customers may rate lower in later reviews. The size of decrease is slightly smaller in the responding group (M = -0.3560) compared to the non-responding group (M = -0.3813), though the difference is less significant (p = 0.0652).

**Table 3. Effect of Providing Responses on Rating Changes**

| Panel A: Rating and rating change between responding and non-responding | | | | | | |
|---|---|---|---|---|---|---|
| | | $Response_{ihv-1}$=0 | | $Response_{ihv-1}$=1 | | T-test |
| Variables | | M | SD | M | SD | t-value |
| $Rating_{ihv}$ | | 4.2449 | 0.9779 | 4.3896 | 0.9038 | -11.3833*** |
| $RatingChange_{ihv}$ | | -0.0562 | 0.9671 | 0.0136 | 1.0358 | -5.1238*** |
| **Panel B: Rating change between responding and non-responding based on previous rating level** | | | | | | |
| | | $Response_{ihv-1}$=0 | | $Response_{ihv-1}$=1 | | T-test |
| Conditions | Variables | M | SD | M | SD | t-value |
| $Rating_{ihv-1}$ = 1 | $RatingChange_{ihv}$ | 1.6714 | 1.4809 | 2.6418 | 1.3157 | -7.0115*** |
| $Rating_{ihv-1}$ = 2 | $RatingChange_{ihv}$ | 1.1916 | 1.2254 | 1.7795 | 1.2140 | -6.0602*** |
| $Rating_{ihv-1}$ = 3 | $RatingChange_{ihv}$ | 0.5173 | 1.0440 | 0.7930 | 1.0738 | -5.9287*** |
| $Rating_{ihv-1}$ = 4 | $RatingChange_{ihv}$ | 0.0676 | 0.8669 | 0.1662 | 0.8696 | -4.6354*** |
| $Rating_{ihv-1}$ = 5 | $RatingChange_{ihv}$ | -0.3813 | 0.7531 | -0.3560 | 0.7417 | -1.8439* |
| **Panel C: Rating change between responding and non-responding based on number of visits** | | | | | | |
| | | $Response_{ihv-1}$=0 | | $Response_{ihv-1}$=1 | | T-test |
| Conditions | Variables | M | SD | M | SD | t-value |
| Visit = 2 | $RatingChange_{ihv}$ | -0.0638 | 0.9818 | 0.0196 | 1.0530 | -5.5675*** |
| Visit > 2 | $RatingChange_{ihv}$ | -0.0032 | 0.8561 | -0.0152 | 0.9483 | 0.3670 |

Note: Response is a dummy variable, indicating whether the previous review has been responded to. Visit denotes customer i's review of $v^{th}$ stay with hotel h. * p < 0.1, ** p < 0.05, *** p < 0.01

In addition, we also examined the ratings of repeat reviewers based on the number of reviews they have written. In our sample, 91.88% of reviews are the first two reviews provided by customers of the same hotel, and only 8.12% of reviews are given by customers regarding later stays (visit $\geq 3$). The results in Panel C of Table 3 reveal that there is a significant difference in rating changes between responding (M = 0.0196) and non-responding (M = -0.0638) for customers who review the same hotel twice. However, we do not observe a similar statistical significance when a reviewer has multiple reviews (more than three reviews) for the same service provider (p = 0.7136). This suggests that managerial intervention has limited power to influence review ratings provided by customers who have a great deal of experience with the service provider.

The above analysis suggests that customer ratings may improve without management providing responses to online reviews. Nevertheless, intervention by the service providers may amplify such improvement or mitigate a decrease in ratings. This implies that providing responses is favourable for enhancing future satisfaction and online ratings, especially to low satisfaction customers. For customers who have multiple stays with and reviews for the same service provider, the influence of management responses on future ratings seems trivial.

### 4.3 Impact of Response Styles

In addition to the receipt of management responses, customers may also interpret managerial efforts differently depending on how the responses are written. To test this, we first identified two situations: First, when the customer's subsequent rating of the same hotel remains unchanged or has increased compared to his/her earlier review rating (Increase = 1). Second, when the subsequent rating is lower than before (Increase = 0). As can be observed in Table 4, the differences in response length and response sentiment between the two groups are significant. First, when ratings are improved, we observe that the length of the responses to previous reviews is longer. This is potentially reflective of managerial effort to explain the situation in greater detail to restore customer satisfaction. Second, the average sentiment for groups is at approximately the same level, although it is slightly lower in the ratings improvement situation (the difference between the two means is 0.01). It is a demonstration of possible difference in response content and tones between the two situations. In the ratings improvement scenario, the service provider may put more effort into addressing customers' concerns and thus, the responses are more narrative in comparison to the "hollow" expressions used in extremely positive responses, leading to a minor decrease in sentiment level. Furthermore, we do not observe a statistically significant difference in response days between the two groups, though response speed is higher when Increase =1. One possible explanation is that hotels in our sample tend to provide prompt responses (overall M = 12.15), regardless of the level of customer satisfaction.

**Table 4. Effect of Responses Styles on Rating Improvement**

| | Increase=0 | | Increase=1 | | T-test |
|---|---|---|---|---|---|
| Variables | M | SD | M | SD | t-value |
| $ResponseDays_{ihv-1}$ | 13.5744 | 69.3080 | 11.7975 | 64.6583 | 1.1839 |
| $ResponseLength_{ihv-1}$ | 82.3733 | 45.7335 | 86.1141 | 47.3268 | -3.3490*** |
| $ResponseSentiment_{ihv-1}$ | 0.7057 | 0.0983 | 0.6955 | 0.1111 | 4.1251*** |

Note: Increase is a dummy variable, indicating whether a customer's rating of hotel h has increased (increased or unchanged) or decreased compared to his/her previous rating of the same hotel. We also test LnResposneDays and the result is not significant either. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Moreover, the changes in ratings may further affect response styles, if the service providers identify the repeated reviewers. We tested this by conducting a two-sample t-test and analysis of variance (ANOVA). The results are presented in Table 5. First, there is no significant difference in response provision and response speed between the ratings increase and decrease situations. This demonstrates that regardless of the level of subsequent ratings, firms' decision to respond and the promptness of their responses are likely to be unaffected. However, when customer ratings are lower compared to previous ratings, the length of the response tends to increase ($t = 23.3288$, $p < 0.01$; $F(1, 13235) = 544.23$, $p < 0.01$). When a firm receives complaints from returning customers, whose opinions are potentially more influential, they may write longer responses to explain problems and perform service recovery. Moreover, the sentiment of managerial responses is higher in the ratings improvement group ($t = -33.3969$, $p < 0.01$; $F(1, 13235) = 1115.35$, $p < 0.01$). Given that customer satisfaction has been improved, the service providers may respond in a more positive tone to show appreciation for customers' return and higher rating.

**Table 5. Impact of Rating Change on Responses Styles**

| | Increase=0 | | Increase=1 | | T-test | ANOVA |
|---|---|---|---|---|---|---|
| Variables | M | SD | M | SD | t-value | F-value |
| $Response_{ihv}$ | 0.6080 | 0.4883 | 0.6017 | 0.4896 | 0.7647 | F (1,21949) = 0.58 |
| $ResponseDays_{ihv}$ | 8.0011 | 20.2949 | 7.6051 | 25.7695 | 0.7487 | F (1,13235) = 0.56 |
| $ResponseLength_{ihv}$ | 103.5101 | 56.7416 | 80.8971 | 41.7883 | 23.3288*** | F (1,13235) = 544.23*** |
| $ResponseSentiment_{ihv}$ | 0.6390 | 0.1363 | 0.7138 | 0.0947 | -33.3969*** | F (1,13235) = 1115.35*** |

Note: Increase is a dummy variable, indicating whether a customer's rating of hotel h has increased (increased or unchanged) or decreased compared to his/her previous rating of the same hotel. We also test LnResposneDays and the result is not significant either. * p < 0.1, ** p < 0.05, *** p < 0.01.

## 5 Discussion and Implications

Compared to the previous approach of offline comments, harnessing social-media-oriented data text analytics on online platforms to inform firms' decisions and strategy has been found to be beneficial (e.g., Liu et al., 2018; Xiang et al., 2015). Nevertheless, much of the current literature overlooks the effects of online managerial response on returning customers' future satisfaction (review ratings). Thus, our study fills a void within the literature. Our analysis indicates that there is a meaningful difference in customer ratings depending on whether or not they receive a response to their online reviews, as well as whether the response styles have a meaningful impact on ratings improvement.

The main research findings are summarised below. Customers' future ratings of a service provider increase when their previous reviews receive a response from the service provider. This is in accordance with existing studies (Gu and Ye, 2014; Sparks, So and Bradley, 2016; Proserpio and Zervas, 2017), which have found that managerial responses have a positive impact on customers' future ratings. However, we also observe that the influence is less significant for high satisfaction customers and loyal customers with multiple (more than three) stays and reviews, than for low-satisfaction customers and one-time visitors/reviewers. This finding differs from that of Wang and Chaudhry (2018), whose work determined that management responses to positive reviews have a negative effect on subsequent ratings. This may be explained by the fact that satisfied customers often leave positive comments and high review ratings and therefore, it is difficult to further increase the ratings for this group of customers. However, the continuous provision of positive reviews from satisfied customers certainly plays a significant role in improving firms' brand image and attracting potential customers. Second, loyal customers may have established strong relationships with hotels and are thus, more likely to evaluate service based on their experience during their stay. As a result, hotels' online management responses to their reviews have less of an impact. Nevertheless, having more positive reviews and a higher number of 5-score ratings may significantly affect future ratings through social dynamics (Moe and Trusov, 2011).

In addition, we find that management response styles are different between ratings improvement and non-improvement scenarios. To be specific, managerial responses tend to be longer and exhibit slightly less positivity in the ratings improvement scenario than in the non-improvement scenario. This implies that more detailed management responses with specific textual content are more likely to have a positive impact on the future ratings of repeat customers. Conversely, the sentiment of the responses may not have such a significant impact, especially with regard to polite and positive responses. Interestingly, we also find that response speed has no significant effect on either ratings improvement or non-improvement scenarios. This finding supports the view of Min, Lim and Magnini (2015), who also found no influence of response speed on ratings. However, this finding contradicts that of Wang and Chaudhry (2018), who have suggested that management responses to negative reviews should be timely so that they are visible to subsequent reviewers.

Moreover, we also observe that changes in subsequent customer ratings also affect the response styles to current reviews. More specifically, when a customer's review rating has increased, the management response to the current review of the customer is shorter and more positive. This finding is reflective of the fact that the response style to an online review depends on the nature of the review (Xie et al., 2016). The length and sentiment of the response are pertinent to the content and tone of the review. However, response provision and speed are not affected by whether or not ratings improve. One possible explanation is that the decision to provide a response is dependent on firms' overall online review intervention strategy and their resources (van Noort and Willemsen, 2012), rather than changes in customer satisfaction reflected in review ratings.

These findings offer important managerial implications to the hospitality and tourism sector for improving future customer ratings and managing reviews of regular reviewers. First, providing responses, especially longer positive responses, is effective in improving customers' subsequent review ratings, particularly with regard to low-rated reviews.

Furthermore, it is worth identifying repeated reviewers, as the impact of managerial responses is weaker on returning customers. Nevertheless, it is beneficial to incentivise returning customers to continue writing positive reviews. It is also important to allocate resources and efforts to managing new online reviews. These insights are beneficial for managers to develop appropriate management response strategies to protect and develop a firm's online reputation and future marketing strategies. Moreover, due to growing concerns about privacy and ethics regarding social media data analytics (GBDR, 2018), a firm must be careful to not abuse their responsibility while reaping the benefits of the accumulated knowledge. It is important for companies to be transparent about their customer data collection and usage practices.

The study contributes to the emerging literature on the use of big data text analytics and value creation through the utilization of big data. We have integrated knowledge based, dynamic capabilities perspectives with research on big data and in doing so, we examined the effects that management response has on the subsequent ratings of repeat reviewers by utilising social media text analytics and thus, demonstrating its utility in the creation of value through both structured and unstructured data (e.g., Chen et al., 2012; George et al., 2014; Khan and Vorley, 2017). This is one of the first studies to examine the effect of online managerial responses on returning customers' future satisfaction on a large scale data taken from a diverse set of hotel chains, thus offering deeper insights how hotel chains can enhance business value through harnessing textual online analysis. Despite the valuable insights offered by the study, however, there are several limitations of this study. We did not examine the causal relationship between managerial response and ratings improvement, given that repeat customers may have strong opinions on service experience and individual reviewer characteristics (e.g., personal preference in review ratings) are unobservable to researchers. Rating improvement can be due to a variety of factors (e.g., improvement in service quality, time trend), so the results need to be interpreted with caution. Furthermore, without sales data, it is difficult to come to any conclusions regarding the economic impact of management responses. The use of online review data alone cannot address these limitations. Despite the managerial insights derived from the analysis of a large volume of user-generated content, it is critical to incorporate other forms of data (e.g., firms' operational and transactional data) to maximise the value of social media research. Due to the rise in global tourism, customers vary thus examining the specific language use in reviews and linking it individual and collective dimensions of culture may provide additional insights into online reviews and future ratings.

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