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Abstract:

In the era of electronic word-of-mouth, firms face pressure to respond to online reviews strategically to maintain and enhance their reputation and financial viability. With guidance from service recovery theory and affect theory, we developed a framework that classifies management responses to seek actionable opportunities to improve firm performance. Using 37,896 managerial responses to online reviews for 390 hotels in three U.S cities, we employed text-mining techniques such as sentiment analysis and topic modeling to develop a framework that classifies the responses into four categories: acknowledgment, account, action, and affect. We evaluated this framework's effectiveness on subsequent reviews and hotel revenue. Among the management response characteristics, we found that acknowledgment and action were significantly associated with future review ratings. Furthermore, hotel class moderated the relationships between these characteristics and hotel revenue. This study provides recommendations to firms about how they can manage their resources to manage responses to online consumer reviews toward increased financial performance.

Keywords: Managerial Responses, Text Mining, Financial Performance, Response Framework.

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1 Introduction

Online word-of-mouth (WOM) has become a key component in business due to social media's fast growth and reach. The literature has shown that WOM across social media and other online platforms can have a significant impact on a firm's performance (Chintagunta, Gopinath, & Venkataraman, 2010; Duan, Gu, & Whinston, 2008; Godes & Mayzlin, 2004). As a result, many managers today take a proactive role in responding to online consumer reviews. Due to their visibility and transparency, online managerial responses (OMRs) not only affect consumers who submit the reviews but also influence the behavior and satisfaction of subsequent consumers who observe them (Gu & Ye, 2014). Therefore, as a managerial intervention strategy, OMR plays an important role in shaping a firm's reputation. It does so by amplifying the beneficial effects of positive reviews and minimizing the detrimental effects of negative reviews on a firm's brand perception (Sparks & Bradley, 2017).

Several studies have investigated the effect that managerial responses have on consumer satisfaction and firm reputation (e.g., Chen, Gu, Ye, & Zhu, 2019; Chevalier, Dover, & Mayzlin, 2018; Gu & Ye, 2014; Proserpio & Zervas, 2017; Wang & Chaudhry, 2018; Xie, So, & Wang, 2017; Xie, Zhang, Zhang, Singh, & Lee, 2016). While these studies contribute to our knowledge about OMRs, they lack in three aspects. First, prior studies have primarily exploited reviews' numerical aspects and their subsequent responses. In this way, they have neglected their textual aspects and, thus, significantly diminished their ability to present a holistic understanding. Little research has analyzed OMRs' content and sentiment. Second, prior studies reveal that it is the strategy in which hotel management composes and disseminates responses rather than response frequency that contributes to consumers' perceptions of these responses (e.g., Wang & Chaudhry, 2018). Yet, these studies have not fully discussed how different strategies of OMRS may relate to subsequent consumer satisfaction in different ways. As an exception, Sparks and Bradley (2017) developed propositions regarding which types of responses to negative reviews would be more effective in improving customer satisfaction. However, their propositions only focused on responses to negative reviews and they did not empirically test them. We still lack clear understanding about which strategies firms should adopt to improve their performance as opposed to simply mitigating damage. Third, studies have predominantly focused on the impact that managerial responses have on consequent consumer review behaviors and satisfaction rather than business performance. Studies have not fully explored whether and how management response relates to business performance such as revenue.

To fill these gaps, we examine two research questions (RQ):

RQ1: Can we design a framework that quantifies managerial responses based on their sentiment and semantic aspects?

RQ2: If we can design such a framework, can we use it to investigate the relationship between managerial response strategies and business performance in terms of subsequent consumer reviews and revenue?

To address these questions, we first draw concepts from service recovery literature, affect theory, and social exchange theory to quantify semantic and sentimental aspects of managerial responses to online reviews. From these aspects, we derive a textual analytics framework based on various managerial response dimensions such as acknowledgment, account, action, affect, and congruence (similarity between the review and response). We then empirically examine whether OMRs indeed relate to business performance. We collected 37,896 managerial responses to consumer reviews retrieved from 390 hotels from TripAdvisor that we matched to their quarterly revenues. With this dataset, we could test our text analytics framework's effectiveness on two levels: consumer-level reviews and hotel-level revenue.

We found that responding strategies that OMRs' content and sentiment reflect play an important role in improving subsequent consumer ratings and hotel revenue. We found that managerial response aspects (acknowledgment, account, action, affect, and congruence) relate to consumer satisfaction and hotel revenue in different ways. Offering future action in a managerial response may increase subsequent consumer satisfaction, while merely acknowledging the problem may decrease subsequent consumer satisfaction. When it comes to revenue, hotel class moderated the relationship between OMRs and revenue. Higher-tier hotels (hotel class > 3.5) may benefit from increasing congruence, account, and affect in their OMRs, while such behavior may not be important or even harmful for lower-tier hotels. Instead, lower-tier hotels should focus on acknowledging the problem and providing actions. We found both acknowledging and providing actions to positively relate to revenue with lower-tier hotels; however, such effects may diminish or even become negative when higher-tier hotels conduct such actions.

Our study contributes to both literature and practice. First, we adopt and advance the AAA framework that Sparks and Bradley (2017) developed and implement a more comprehensive text analytical framework that classifies OMRs based on responses' semantic and sentiment aspects and their alignment with reviews. Second, we fill the gap in current social media research by showing how response strategies can influence not only subsequent consumer reviews but also tangible business performance such as revenue. Finally, we offer managerial guidance and strategies on how to effectively respond to consumer reviews on social media platforms.

This paper proceeds as follows: in Section 2, we review the literature related to and theories of managerial responses. In Section 3, based on these theories, we develop our text-based analytical framework. In Section 4, we describe the data and the procedures we followed to implement our framework. In Section 5, we evaluate the framework by discussing its effectiveness in driving subsequent consumer ratings and hotel revenue. In Section 6, we discuss the implication of our findings. Finally, in Section 7, we conclude the paper.

2 Literature Review

2.1 Online Managerial Responses (OMRs) for Service Recovery and Reciprocity

Managers can use online responses to consumer reviews to achieve two distinct objectives. First, managers respond to online reviews to address consumers' negative comments so that their firm can retain disgruntled consumers but also mitigate any dissuasive properties negative reviews may have on future consumers (Miller, Craighead, & Karwan, 2000). We can explain such responses with the service recovery theory (Gronroos, 1988). Second, OMRs may also strengthen the influence that positive online consumer reviews have on a business (Xie, Zhang, & Zhang, 2014). We can explain those responses with social exchange theory (Blau, 1964). We review both theories in this section.

We define service recovery as the action a service provider takes to address consumers' complaints (Gronroos, 1988). We review literature in service recovery to identify key themes that one could use in developing a framework that captures aspects of responses to negative reviews. Researchers have attempted to categorize service-recovery strategies (Bradley & Sparks, 2012, 2009; Davidow, 2000; Mok, Sparks, & Kadampully, 2013). Traditional offline service-recovery mechanisms focus on two components of organizational responses to service failures: 1) the mechanics of responding and 2) responses' content. The mechanics of responding concerns the response's promptness (Davidow, 2000) and the effort a business spends to respond (Karatepe, 2006). Regarding responses' content, research has generally characterized business responses in terms of apology, redress, facilitation, credibility, and attentiveness (Davidow, 2000). Research has found these aspects except facilitation to have significant effects on consumer satisfaction (Davidow, 2000). More recently, Sparks and Bradley (2017) developed an acknowledgments, accounts, and actions (AAA) typology of managerial responses to negative online reviews. We use these components as a grounded typology to build our textual analytics framework.

In contrast to negative reviews, one can use social exchange theory to describe responses to positive reviews. This theory proposes that social behavior results from exchange processes (Blau, 1964). Reciprocity between managers and consumers critically affects knowledge sharing in a community (Lechner & Hummel, 2002). When managers reply to positive reviews, it signals that they are trying to learn from consumers (Lechner & Hummel, 2002), express their appreciation, and establish ties with their consumers (Xie et al., 2014). Such reciprocity can further promote and influence consumers' positive perceptions (Harrison-Walker, 2001) and, thus, reinforce positive reviews from consumers.

2.2 Impact of Online Managerial Responses on Consumer Satisfaction

Since consumers can publicly see managerial responses to other consumers' reviews, such responses can prove more telling than the reviews themselves to potential consumers. Potential consumers have a two-fold interaction process with OMRs: 1) before they make a purchase (in terms of reading existing reviews to aid in the purchase decision-making process) (Wei, Miao, & Huang, 2013) and 2) after they make a purchase (in terms of revisiting hotels' platform to add their own reviews) (Wang & Chaudhry, 2018). When managers respond to negative reviews, their effort can improve complaining consumers' retrospective satisfaction by moderating how they perceive justice and fairness (Mccoll-Kennedy & Sparks, 2003). Moreover, subsequent consumers can identify whether a hotel adequately provides solutions to service failures (Lee & Song, 2010), and these perceptions can further determine their subsequent reviewing behaviors (Sparks, So, & Bradley, 2016; Wang & Chaudhry, 2018). When hotel managers respond to positive reviews, their responses can also affect both reviewers' and prospective consumers' perceptions. These responses can establish warm human connections between the business and its reviewers (Xie et al., 2014), who will be more likely to provide positive reviews in the future. Prospective consumers also benefit from OMRs to positive reviews as they can observe whether hotel managers commit to maintaining the service quality in their response (Xie et al., 2014).

As such, regardless of online reviews' valence, managerial responses serve as a powerful reputation-management tool. Recent studies have empirically confirmed OMRs' effects on future consumer satisfaction. While some studies have found that managerial responses only increase the future satisfaction of consumers who have had low satisfaction with their prior experience (Gu & Ye, 2014), others have found OMR adoption to have a generally positive impact on subsequent review valence and volume. For example, Proserpio and Zervas (2017) and Ananthakrishnan, Proserpio, and Sharma (2019) both found that the presence of OMRs increased subsequent hotel consumer reviews' valence. Xie et al. (2016) found that a higher response ratio increased both the valence and volume of subsequent reviews. Chen et al. (2019) observed that OMRs had a positive on subsequent review volume but no significant impact on subsequent reviews' valence. In contrast, Chevalier et al. (2018) provided evidence that management responses impact ratings negatively. Wang and Chaudhry (2018) argued that we can explain such conflicting results by investigating the effect that OMRs have on positive and negative reviews separately. They found that OMRs have a positive impact on negative reviews but a negative impact on positive reviews.

2.3 Impact that Online Managerial Responses have on Business Performance

While earlier studies focused more on consumers' perceptions and behaviors, some more recent studies have investigated the impact that managerial responses have on business performance. For example, researchers have found that timeliness and length of manager responses to online reviews positively relate to hotels' revenue (Xie et al., 2017). However, a simple increase in the number of managerial responses does not result in increased business performance (Xie et al., 2014). This finding may suggest that the effectiveness of managerial responses depends on response strategies rather than response frequency. Kumar et al. (2018a) found that a business owner's responses to reviews play a significant role in how well the focal and nearby businesses perform. Kim, Lim, and Brymer (2015) reported a positive relationship between response rate to negative online reviews and hotel revenue. However, to the best of our knowledge, no prior study has considered how the qualitative textual aspects in OMRs impact business performance such as revenue.

3 Proposed Framework Development

Compared to traditional offline service recovery and social exchange, online forums allow potential consumers to view managers' interaction with consumers. Therefore, we conceptualize OMRs in a way that encompasses both the aspects that the literature has explored and the aspects that pertain specifically to online forums.

In this paper, we extend the AAA framework that Sparks and Bradley (2017) developed. They developed the AAA typology with key constructs from the service recovery literature (Davidow, 2000) and classified managerial responses to negative online reviews into three categories: acknowledgments (responses that acknowledge the dissatisfying event), accounts (responses that account for a dissatisfying event's occurrence), and actions (responses that discuss actions to address the complaints).

Despite its wide adoption in classifying managerial responses (Bonfanti, Vigolo, & Negri, 2016; Sparks et al., 2016; Xie et al., 2017), this typology has two gaps that we fill in this work. First, the typology's focus on OMRs to negative responses limits its applicability to service recovery and, thus, does not consider other response aspects that service recovery theory does not explain. Second, the typology focuses mostly on responses' content; namely, on *what* managers respond with rather than *how* they do so. In Sections 3.1 and 3.2, to fill these two gaps, we extend the framework to include two response quality-related aspects: 1) *affect* in the response and 2) the *congruence* between a response and its matching review.

3.1 First Addition to the AAA Typology: Affect-Enriched Response to Review

Affect refers to a set of concepts that include emotions, moods, and feelings (Bagozzi, Gopinath, & Nyer, 1999; Frijda, 1988; Russell, 2003). Researchers commonly consider it an umbrella term that encompasses two main components: 1) short-term feeling states such as emotions and feelings and 2) long-term feeling traits (i.e., a person's tendencies to feel and act in certain ways) (Watson, Clark, & Tellegen, 1988). In this study, since consumers can only observe short-term emotions in OMRs, we focus on short-term emotions and moods.

The AAA typology focuses mostly on responses' content. However, affective information also plays a critical role in decision making (Cambria & White, 2014). Scholars have found that emotions and feelings can influence economic choices (Rick & Loewenstein, 2008), relationship quality (Ekman, 2003; Keltner & Lerner, 2010), policy choices (Small & Lerner, 2008), and conflict resolution (Barsade & Gibson, 2007). In our context, managers often integrate emotions into their responses, which can impact consumers' attitudes when they read such responses.

On the one hand, when a manager posts a response to a negative review, the manager typically does so to resolve a conflict. Scholars have observed the effect that emotions, such as compassion, have in conflict resolution and negotiations (Allred, Mallozzi, Matsui, & Raia, 1997). Similarly, Min, Lim, and Magnini (2015) found that, when managers provide an empathetic statement, consumers perceive the responses to complaints as more positive. Thus, the emotions that responses reflect can affect how complaining reviewers feel about the way in which an organization hears and resolves issues.

On the other hand, when replying to positive reviews, managers usually express their appreciation, gratitude, and happiness. Positive emotions in a response might affect consumer decisions as well. For example, sales professionals often use upbeat, enthusiastic expressions with their consumers to encourage purchasing behaviors (Pugh, 2001; Totterdell & Holman, 2003). From a social exchange theory perspective, reciprocity in kind is one of the best-known exchange rules (Cropanzano & Mitchell, 2005). When receiving positive rewards, social actors tend to respond to such kindness with similar benevolence, which creates self-reinforcing cycles (Cropanzano & Mitchell, 2005). Therefore, when receiving a positive review, managers need to incorporate similar, positive affectations in their responses to establish a positive reciprocal relationship with their consumers. As such, we expect that affective information expressed in OMRs to both positive and negative reviews affects consumers' perceptions. We capture such information in our framework.

3.2 Second Addition to the AAA Typology: Topic Congruence between Review and Response

Congruence refers to how closely the topics in an OMR resemble the topics in its corresponding consumer review. Consumers expect firm representatives to put a great deal of effort into resolving their individual issues (Blodgett, Hill, & Tax, 1997; Tax, Brown, & Chandrashekaran, 2006). When managers provide basic and generic responses that do not specifically pertain to the issues that consumers raise, reviewers and potential consumers perceive the managers as making low effort (Wei et al., 2013). Conversely, when managers respond to specific issues in consumer reviews by repeating or paraphrasing them, they can send reviewers and potential consumers a signal that the business takes consumers' voices seriously and puts much effort into solving consumers' problems (Min et al., 2015). Empirically, Wei et al. (2013) found that consumers desire specific managerial responses more than generic responses to negative reviews. Similarly, Min et al. (2015) report that a paraphrasing statement in a response has a significant positive influence on potential consumers' satisfaction.

We summarize the key OMR constructs in our framework and their guiding theories in Table 1. In Section 4, we discuss how we used text analytics methods to measure the OMR constructs in our framework.

Table 1. OMR Constructs

Constructs	Guiding theory
Acknowledgment	Service recovery theory and the AAA framework
Account	Service recovery theory and the AAA framework
Act	Service recovery theory and the AAA framework
Affect	Service recovery theory and affect theory
Topic congruence	Service recovery theory and reciprocity theory

4 Methodology of Textual Analytics for Consumer Reviews and OMRs

4.1 Data

The hotel business is a salient context in which consumers write reviews about their experience and managers respond to these reviews to recognize feedback and seek opportunities to improve services. We focus on three major hotel markets in Texas in the United States (US): Austin, Fort Worth, and San Antonio. These geographically dispersed markets have an active hotel presence, which provides a good research context to observe how individual hotels' online presence influences their offline performance. Because Texas's Comptroller Office mandates that hotels must disclose their revenue for tax purposes, these three markets provide access to the highly disaggregated performance data at the individual hotel level that one could not access for other markets. Taken together, the market characteristics and data availability make the three markets an ideal research setting for our study.

Our data comes from two sources. First, we collected consumer reviews and managerial responses from Tripadvisor, a major website in the US where hotel managers can access publicly displayed consumer reviews on their businesses. As of December 2019, Tripadvisor offers access to more than 830 million reviews on 8.6 million accommodations, restaurants, airlines, and experiences (Tripadvisor, n.d.). For each hotel in our sample, we collected the time-stamped reviews that each comprised review text and an associated overall rating and subratings (i.e., ratings of value for money, location, rooms, cleanliness, and employee services) on a five-point scale (1 = terrible to 5 = excellent). Managerial responses appeared as text underneath each review. For the three cities we examined, Tripadvisor hosted 98,371 reviews for 597 individual hotels. Among these reviews, 37,896 reviews from 390 hotels had received a managerial response.

Second, we obtained quarterly archived data on hotel revenue from Texas's Comptroller Office. The Texas Comptroller of Public Accounts furnishes the data in their capacity as state tax collection auditors. In addition to quarterly hotel room revenue, the data set includes basic information such as hotel name, address, capacity (or the number of hotel rooms), how many years a hotel has existed for, and the hotel's scale or class (luxury, economy, etc.). The raw data set spans the period from January, 2003, to August, 2014. Our sample covers 597 hotels in three cities (Austin, Fort Worth, and San Antonio) over a period from the first quarter in 2009 to the second quarter in 2011. We combined the hotel revenue data with the data on reviews and responses to construct a panel at the hotel by quarterly year level.

4.2 Text-mining Tool

To analyze and classify both consumer reviews and managerial responses using natural language processing (NLP), we adopted IBM's SPSS Modeler v.18.0 over other unsupervised latent Dirichlet allocation (LDA) model-based software packages (Blei, Ng, & Jordan, 2003) for three reasons. First, SPSS Modeler provides various linguistic-based text mining techniques such as keyword extraction, clustering, association analysis, categorization, summarization, and visualization (Tang & Guo, 2013). These text-mining techniques can collectively work together to explore keywords and identify semantic topics and other patterns in text. Second, while LDA model-based text mining tools usually do not take into account domain-specific context, SPSS Modeler has a well built-in domain-specific vocabulary and other linguistic resources to more precisely recognize textual data in a particular business domain. For example, SPSS Modeler has a built-in "hotel satisfaction" resource that helps researchers effectively explore groups of keywords in the hotel satisfaction context in regards to food, location, budget, service, and so on. This resource ensures that the program not only analyzes keywords by their frequency but also recognizes and groups them based on their semantic meaning in a specific domain[1] (Berezina, Bilgihan, Cobanoglu, & Okumus, 2016). Third, SPSS Modeler supports rule-based topic modeling for pre-defined semantic topics. By using this function, we could incorporate the topics into our model that we derived from existing studies on reviews and responses. For example, we could manually create a regular expression rule for the topic "service", a common topic in hotel reviews. When a review met the specified rule, we categorized it as expressing an opinion towards the corresponding hotel's service.

[1] For example, the built-in resource groups words such as "front desk" and "room service" under the "service" keyword group.

4.3 Conducting Text Mining on Consumer Hotel Reviews

4.3.1 Preprocessing Consumer Reviews

We first randomly selected 30 percent of consumer reviews from each city in our data regardless of whether the review received a response or not. In this way, we could extract as many topics as possible from the reviews so that the outcome topic list did not only contain reviews that received a response. As a result, we obtained a sample dataset that contained 29,230 consumer reviews. Then, we pre-processed the textual review data. We tokenized the text reviews into words and phrases and deleted stop words such as "and", "the", and "a" in addition to domain-specific stop words. We develop a domain-specific custom stop word list by manually going through the most frequently occurred words in the tokenized word list and identifying the ones that lack meaning in our context. Such stop words did not semantically contribute to the reviews, such as "hotel", "stay", and "days". Finally, we performed stemming in that we reduced each word variant to its base form (Krovetz, 2000). This processing resulted in a clean textual dataset that we could use to model topics in consumer reviews.

4.3.2 Modeling Topics in Consumer Reviews

To extract topics from consumer reviews, we needed to identify: 1) topics that the reviews expressed and 2) the descriptors that represented a particular topic. A descriptor can be a keyword or phrase, a keyword group (e.g., the "service" group), or a regular expression rule (see more details in Table A1 in the Appendix). We identified topics and the underlying descriptors for each topic from the review text in a rule-based and semi-supervised fashion. The following steps describe how we conducted our topic modeling.

Step 1: identify initial topics. We initially created eight different topics that consumer hotel reviews address based on topics that prior studies have identified and that social media platforms commonly use for travel. From a hotel complaint forum, Lee and Hu (2005) classified consumer complaints to hotels with 18 pre-defined problematic categories. They found that the categories that are associated with most complaints were: service provided not agreed on, service declined in quality, rude consumer service representatives, service never provided, and overcharged. By analyzing extremely negative hotel reviews, Levy, Duan, and Boo (2013) identified three overarching issues that consumers raise: hotel, room, and staff. In practice, reviewers on Tripadvisor can provide ratings to six specific areas: location, sleep quality, value, cleanliness, service, and room. Therefore, we considered eight initial topics: 1) cleanliness, 2) service, 3) personnel, 4) value, 5) room, 6) location, 7) amenities, and 8) sleeping quality. These topics overlap in the literature and in practice. We later added more topics that emerged when we developed descriptors for each initial topic.

Step 2: develop descriptors for the initial topics. Next, we focused on developing descriptors for each initial topic. To mine patterns and relationships from our text review data, we used two methods: text-link analysis and clustering analysis based on the "hotel satisfaction" resource template in SPSS Modeler to best calibrate our text mining to the consumer hotel review context. The text-link analysis identified frequent keyword pairs that occurred together in reviews for a particular topic. For example, "location" and "good" appeared together 753 times in the reviews. Thus, this emergent pattern constituted a candidate descriptor for the topic "positive location". Similarly, clustering analysis looks for word pairs that frequently co-occurred in reviews. Then, we grouped similar keywords into clusters by aggregation based on their pairwise similarity values. For example, a cluster of keywords emerged from the reviews: "excellent", "hotel", "stay", "room", "clean", "good", "friendly", and "riverwalk". We mapped these words into four potential topics: experience, cleanliness, personnel, and location. Table A1 in the Appendix provides example descriptors that we assigned to each topic with different techniques.

Step 3: identify new additional topics. Subsequently**,** we reviewed patterns that we identified in the second step and assigned them to a relevant topic based on their frequency and their conceptual meanings. If a frequent pattern derived from the reviews did not fit into any of the initial topics, we created a new topic. In this step, six additional topics emerged: quietness, recommendation, restaurant, Internet, view, and experience. Hence, the eight topics we initially identified increased to 14 topics.

Step 4: extend descriptors for topics. Finally, we used SPSS Modeler's built-in function to automatically extend the identified descriptors for each topic based on three linguistic-based methods (concept inclusion, concept derivation, and semantic networks) to automatically fine-tune a more complete set of descriptors for each topic (see illustrative examples in Table A2 in the Appendix).

Table A3 summarizes the algorithm that we used to create new topics and assign descriptors to each topic. We conducted this process iteratively until no new pattern or new topic emerged. By that point, we had categorized 99.7 percent of the reviews with at least one of the 14 topics we created earlier. Figure 1 summarizes the steps in our topic modeling. The 14 topics each had two sentiment-oriented levels: positive and negative. Thus, the final topic list in our study included 28 topics[2] that 189 unique descriptors (words, word types, rules) identified. Table A4 in the Appendix lists these topics, example descriptors, and example reviews.

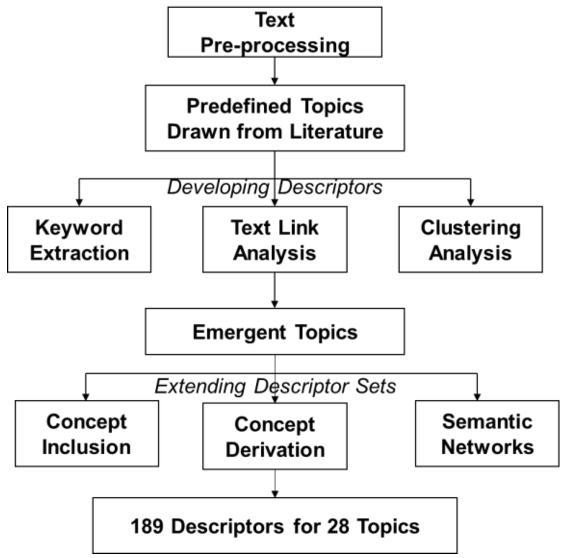

Figure 1. Topic Modeling Steps to Hotel Reviews

4.3.3 Analyzing Sentiment in Consumer Reviews

To quantify each review's sentiment, we calculated an aggregate sentiment polarity score for each review based on its topics (Liu, 2010; Pang & Lee, 2004). We adopted the sentiment polarity score that Bautin and Skiena (2008) proposed. They defined polarity score as the ratio between the total occurrences of positive words and the total occurrences of both positive and negative words. To capture each review's sentiment, we adopted this measurement at the topic level by defining the overall sentiment ratio (*SR*), which ranged between -1 and 1, as follows:

> *SR* = (the number of positive topics/the number of total topics) if the number of positive topics > the number of negative topics, or
>
> *SR* = − (the number of negative topics/ the number of total topics) if the number of negative topics > the number of positive topics, or
>
> *SR* = 0 if the number of positive topics = the number of negative topics.

As such, if the SR sign for a review was + (-), its sentiment was positive (negative); SR = 0 indicated neutral sentiment.

To evaluate whether we calculated SR appropriately, we applied this sentimental analysis method to all the 98,371 reviews in the original dataset. Note that we classified each review into one or more topics. The Pearson correlation between overall numeric ratings (consumer star ratings) and SRs of the ratings' corresponding text reviews was 62 percent. This moderate to strong relationship show our sentiment scoring method was appropriate. Table 2 describes the statistics of numeric ratings by the reviews' sentiment score distribution. We can clearly see that reviews that we classified as positive based on textual content had a much higher average numeric rating (4.33) than the reviews that we classified as negative (2.13). The same pattern held for all the other subtopics such as location, cleanliness, and sleeping quality. These findings also demonstrate that our sentiment analysis method worked well.

[2] We also used these topics to classify OMRs later.

Table 1. Descriptive Statistics of the Review Dataset

Textual review topics		Numeric ratings					
		Overall	Location	Cleanliness	Service	Sleeping quality	Value
Positive sentiment (n = 78,371)	Mean	4.33	4.50	4.51	4.51	4.41	4.27
	SD	0.88	0.79	0.81	0.84	0.87	0.92
Neutral sentiment (n = 9,679)	Mean	3.43	4.04	3.77	3.71	3.67	3.43
	SD	1.35	1.10	1.30	1.36	1.30	1.34
Negative sentiment (n = 10,321)	Mean	2.13	3.32	2.58	2.46	2.61	2.27
	SD	1.22	1.30	1.41	1.39	1.35	1.25
Total (n = 98,371)	Mean	4.01	4.33	4.24	4.23	4.18	3.98
	SD	1.20	0.96	1.12	1.16	1.11	1.19

Finally, we applied SR to all 37,896 reviews that received a response in the original dataset. In Figure 2, we distinguish the reviews based on their sentiment orientation that we classified via two different metrics: 1) the sentiment class (positive, negative, neutral) that we extracted from the review text with our framework and 2) the original numeric rating that the review provided. One can see the three sentiment classes (i.e., positive, negative, and neutral) all had similar proportions. The sentiment value method classified more reviews as negative and fewer reviews as positive compared to the numeric star ratings.

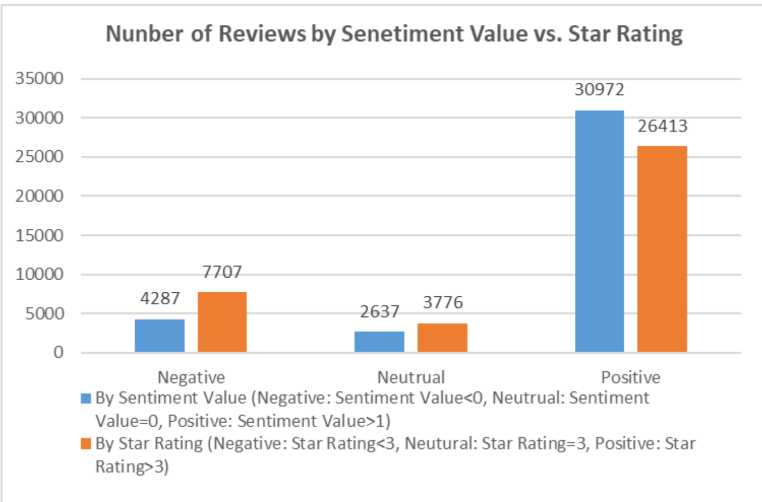

Figure 2. Number of reviews by sentiment value vs. by star ratings

4.4 Conducting Text Mining on the OMRs

Although the procedure to conduct text mining on OMRs resembled the content analysis that we conducted for consumer review data, we needed to model new topics for OMRs in terms of the AAAA typology (recall the AAAA constructs that we created in Table 1) along with the 28 topics that we identified from consumer reviews earlier. To determine whether the content in the reviews resembled the content in their responses, we created a review–response pair similarity score in terms of the 28 topics that we identified earlier. Therefore, in this section, we show how we modeled the new topics in the AAAA typology for OMRs and calculated the topic congruence between review and response.

Step 1: classify OMRs into the AAAA typology. Following a similar logic that we followed to model the 28 topics for consumer reviews previously, we started our OMR topic modeling by identifying potential subtopics for the AAAA (acknowledgment, account, act, and affect) constructs from the literature. We obtained subtopics for acknowledgment, account, and action from the AAA model (Sparks & Bradley, 2017) and from the service recovery literature (Bradley & Sparks, 2009; Davidow, 2000; Miller et al., 2000). In addition, we consolidated a list of subtopics related to affect from the related literature (Bagozzi et al., 1999; Barsade & Gibson, 2007; Russell, 2003; Small & Lerner, 2008; Watson et al., 1988). We identified nine subtopics related to affect that each corresponded to a type of emotion[3]. With the identified subtopics for AAAA, we developed descriptors for each topic by performing word extraction, text-link analysis, and clustering analysis. As before when we conducted text mining on the consumer reviews, new subtopics could have emerged if certain descriptors did not belong to any existing topics. Finally, we again used SPSS Modeler's built-in function to extend descriptors for each topic. As a result, we obtained 17 subtopics for the OMR AAAA constructs, which we summarize in Table A5 in the Appendix.

We then applied this qualifier to all the 37,896 responses to reviews in the original dataset. Of these responses, 89 percent acknowledged the review, while only two percent accounted for the problem. Furthermore, 18 percent provided at least one action, and 19 percent showed at least one type of affect. Table A6 in the Appendix summarizes all four topics along with their subtopics and the percentage of responses (out of all 37,896 responses) each topic identified.

Step 2: calculate the topic congruence. If a manager attempted to address the issues that a review identified by mentioning the same topics, the review and response had a high congruence. Otherwise, they had low congruence. Note that we could have classified each review or each response into the 28 topics that we drew from consumer reviews. We first represent each review (or response) by a vector of the 28 topics. We converted each review (response) into a vector of the 28 topics: T_i={$T_{i,1}$, $T_{i,2}$ ......$T_{i,k}$}, $T_{i,k}$ = 1 if the *k*-th topic was present. Cosine similarity (Charikar, 2002) measures the cosine of the angle between two vectors, and researchers widely use it in text mining in general and to measure topic similarity in particular (Deng, Zheng, Khern-am-nuai, & Kannan, 2019). Therefore, we calculated the cosine similarity in terms of the topics for each pair of the vectors from a review and its response as follows:

$$\text{Cosine similarity } (i,j) = \frac{\sum_{k=1}^{k} T_{i,k} * T_{J,k}}{\sqrt{\sum_{k=1}^{k} T_{i,k}^2}\sqrt{\sum_{k=1}^{k} T_{j,k}^2}} .$$

When the cosine similarity equaled 1, it means the review and response pair expressed the identical topics. When the cosine similarity equaled 0, it means the pair had no topics in common. We calculate this congruence for all 37,896 review-pairs in the original dataset.

Table 3 summarizes the reviews' sentiment, the OMRs' AAAA topics, and the congruence of the pairs in the review-response pair dataset. Interestingly, we found that managers' response content related to action or affect when a review became more negative. A review's sentiment did not seem to change the topic congruence.

Table 3. A Summary of the Content and Sentiment Analysis of all Review-response Pairs

Review type	Positive (n = 30,972)	Neutral (n = 2,637)	Negative (n = 4,287)	All reviews (n = 37,896)
Numeric ratings				
Average Rating	4.31	3.14	2.23	3.99
Review sentiment from text analysis				
Average sentiment	0.91	0	-0.85	0.65
AAAA constructs from responses				
Acknowledgment	89%	91%	89%	89%
Account	2%	4%	5%	2%
Action	15%	27%	33%	18%
Affect	15%	33%	43%	19%
Congruence	0.20	0.16	0.12	0.18

[3] Affect subtopics can show negativity or positivity due to affect's nature.

We summarize the framework in Figure 3. The framework has three major components. First, we developed a topic analysis component that extracts topics from both review and responses. Second, we developed a sentiment analysis component that analyzes reviews' sentiment values based on topics that one extracts from the first component. Third, we developed an OMR responsive analysis component that computes the topic congruence between the review and response. The resulted topic congruence, along with the four AAAA topics from the first component, quantifies OMRs' characteristics. In Section 5, we evaluate the framework by examining the effects that these extracted OMR characteristics had on subsequent consumer ratings and hotel revenue.

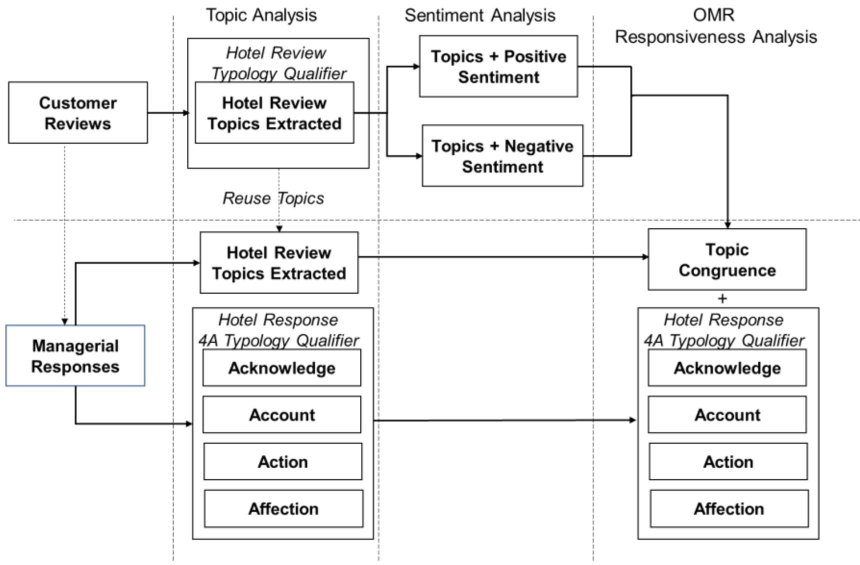

Figure 3. The managerial response framework

5 Evaluation and Results

To evaluate our AAAA framework, we investigated the effect that the OMR characteristics that we extracted with the framework had on subsequent consumer ratings and on hotel revenue. We construct our datasets on two levels: the individual review level and quarterly revenue level. First, to examine how a subsequent reviewer evaluated a hotel based on prior reviews and responses, we began with a dataset that contained all the 37,896 reviews that had a matching response. A review that reviewer *i* at time *t* for hotel *j* generated constituted our unit of observation. To estimate each review's rating, we included five categories of independent variables: 1) a given review's individual characteristics (e.g., length, numeric subratings for specific hotel aspects, and the sentiment that we extracted from the review text), 2) how many reviews the reviewer had posted on the site, 3) the cumulative average characteristics of the reviewer's preceding reviews, 4) the cumulative average characteristics of the hotel's precedent OMRs, 5) and hotel characteristics such as hotel class and size. After removing records with missing values in the numeric subratings, our dataset had 25,258 observations. Table 4 defines the variables and provides their descriptive statistics for these reviews. Table A7 in the Appendix provides the correlation matrix for the variables. Second, to examine how OMRs influenced subsequent hotel revenue, we constructed a second dataset by aggregating the above variables to the quarterly revenue level for each hotel, which resulted in 414 hotel-quarter pair observations. Table 5 defines the variables and their descriptive statistics for this dataset. Table A8 in the Appendix provides the correlation matrix for the variables. In Section 5.1, we discuss the results from the review-level analysis. In Section 5.2, we then discuss the results from the hotel-level analysis.

Table 4. Review-level Variable Definitions and Summary Statistics

Variable	Description	Mean	Std.	Min	Max
Individual review characteristics for hotel *j* at time *t*					
Rating	The overall rating of the hotel	4.07	1.13	1	5
LocationRating	Rating of the hotel's location	4.38	0.90	1	5
CleanlinessRating	Rating of the hotel's cleanliness	4.29	1.04	1	5
ServiceRating	Rating of the hotel service	4.29	1.09	1	5
SleepQualityRating	Rating of the sleep quality of the stay	4.17	1.09	1	5
ValueRating	Rating of the hotel's value	4.01	1.13	1	5
ReviewLength	The number of words in the review text	135.70	123.78	8	2301
ReviewSentiment	Overall SR extracted from the review text	0.67	0.57	-1	1
PastReviews	The number of reviewers' past reviews	24.66	48.93	1	1713
Review environment for hotel *j* until time *t*					
ReviewVolume	The cumulative number of prior reviews	142.23	140.90	1	708
ReviewRating	The cumulative average ratings of prior reviews	3.95	0.56	1	5
Precedent OMR characteristics					
OMRVolume	The cumulative number of prior responses	138.83	139.83	1	707
Acknowledgment	The cumulative portion of OMRs that expressed acknowledgment	0.89	0.13	0	1
Account	The cumulative portion of OMRs that expressed account	0.03	0.05	0	1
Action	The cumulative portion of OMRs that expressed action	0.18	0.15	0	1
Affect	The cumulative portion of OMRs that expressed affect	0.20	0.15	0	1
PositiveAffect	The cumulative portion of OMRs that expressed positive affect	0.14	0.13	0	1
NegativeAffect	The cumulative portion of OMRs that expressed negative affect	0.06	0.08	0	1
Congruence	The cumulative average topic congruence between the reviews and the responses	0.18	0.10	0	1
Hotel characteristics					
HotelClass	Hotel class on a five-point scale that TripAdvisor designated[4]	3.27	0.69	0	4.5
HotelAge	The hotel's age in years	21.10	13.53	0	57
HotelSize	The total number of rooms in the hotel	237.99	177.38	14	1001
HotelAmenities	The total number of amenities in the hotel	8.83	1.73	0	13

Table 5. Quarterly Revenue-level Variable Definitions and Summary Statistics

Variable	Description	Mean	Std.	Min	Max
Rating variables					
ReviewRating	The cumulative average ratings of all prior reviews	3.79	0.52	2.13	5
ReviewVolume	The cumulative number of prior reviews	84.24	83.56	4	558
ReviewLength	The cumulative average length (in characters) of prior reviews	1001.8	488.33	189	3141
OMR variables					
OMRVolume	The cumulative number of prior responses	10.42	15.34	1	124
RespondTime	The cumulative average number of days between the reviews and responses of prior responses	48.94	113.81	1	785.5

[4] 1 = budget traveler hotel, 2 = mid-market economy hotel, 3 = full-service hotel, 4 = above average hotel with some outstanding features and a broad range of services, and 5 = luxury hotel.

Table 5. Quarterly Revenue-level Variable Definitions and Summary Statistics

Congruence	The cumulative average topic congruence between the reviews and the responses	0.16	0.15	0	0.81
Acknowledgment	The cumulative portion of OMRs that expressed acknowledgment	0.74	0.35	0	1
Account	The cumulative portion of OMRs that expressed account	0.07	0.18	0	1
Action	The cumulative portion of OMRs that expressed action	0.27	0.29	0	1
PositiveAffection	The cumulative portion of OMRs that expressed positive affect	0.06	0.14	0	1
NegativeAffection	The cumulative portion of OMRs that expressed negative affect	0.20	0.26	0	1
ResponseLength	The cumulative average length (in characters) of prior responses	532.10	254.91	84.33	2342
Hotel characteristics					
Log(REVENUE)	Quarterly hotel revenue in millions	13.79	1.10	10.83	16.16
HotelClass	Hotel class on a five-point scale that Tripadvisor designated	3.08	0.67	0	4.5
HotelAge	The hotel's age in years	18.89	13.40	0	54
HotelSize	The total number of rooms in the hotel	212.94	145.12	17	1003
HotelAmenities	The total number of amenities in the hotel	8.8	1.99	4	13

5.1 Relationship between Management Responses and Subsequent Consumer Ratings

Following Moe and Schweidel (2012) and Lee, Hosanagar, and Tan (2015), we modeled the rating that reviewer *i* created for hotel *j* at time *t* as:

$$Rating_{i,j,t} = \beta_{1:n_1} X_{i,j} + \delta_{1:n_2} Review_{j,t,(i)} + \gamma_{1:n_3} OMR_{j,t,(i)} + \eta_{1:n_4} HC_{j,t,(i)} + \varepsilon_{i,j,t} \quad (1)$$

where the variable $X_{i,j}$ is a $n_1 \times 1$ vector of reviewer-specific time-invariant covariates that describe the reviewer's experience of the hotel or any observed characteristics of the reviewer. $X_{i,j}$ includes the aforementioned reviewer characteristics. Reviewers may adjust their rating based on how managers have responded to their prior reviews from other consumers. As such, we include $Review_{j,t,(i)}$, which is a $n_2 \times 1$ vector of review environmental covariates including a set of precedent reviewers' rating information (e.g., average rating and the volume of ratings at *t*). $OMR_{j,t,(i)}$ is a $n_3 \times 1$ vector of response covariates at *t* that includes the volume of OMRs and how the manager responded to prior ratings in terms of our AAAA variables and the topic congruence. The term $\varepsilon_{i,j,t}$ is the idiosyncratic error with a mean of 0 and assumed to follow a standard logistic distribution. We estimate the model and present the results in Table 6.

The "Model 1" column in Table 6 shows the results for the basic model specification that excluded the hotel characteristic variables. The second model ("Model 2" column) additionally included hotel characteristics as control variables. Finally, to see whether the results remained consistent after considering reviewers' unobserved baseline positivity (or negativity) at the hotel level, we estimated the full model, which included a random effect of the reviewer's unobserved heterogeneity in the hotel (Gelman & Hill, 2007). We show the results in the "Model 3" column. This final model assumed that a reviewer's unobserved heterogeneity could vary for different hotels because a reviewer's baseline positivity depends on each hotel quality. This final model acted as a robustness check.

Recall that we investigated the effect that account, acknowledgment, action, affect, and congruence (which represent prior OMRs' content aspects) had on subsequent consumer ratings. Acknowledgment and action were statistically significant at $p < 0.05$, while the other variables were not (see Table 6). On the one hand, acknowledgment's negative coefficient indicates that subsequent consumer ratings decrease when prior OMRs include more topics that relate to acknowledgment. In other words, if managers merely acknowledge what reviewers have commented with canned responses that do not address issues that prior consumers raised, future reviewers may adversely react to such responses by lowering their ratings. On the other hand, action's positive coefficient suggests that subsequent reviewers may increase their ratings when the prior OMRs express more toward actionable comments to address any issues that prior consumers raised. Consumers could perceive such efforts as managers' willingness to listen to their customers and improve their service quality.

Table 6. Estimates of Online Management Response Characteristics on Subsequent Ratings

	Model 1		Model 2		Model 3	
DV: rating	Ordered logistic without hotel variables		Ordered logistic with hotel variables		Multilevel mixed-effects ordered logistic	
	Estimate	S.E	Estimate	S.E	Estimate	S.E
Individual review characteristics for hotel *j* at time *t*						
Subratings[5]	Controlled		Controlled		Controlled	
ReviewLength	-0.0015***	(0.0001)	-0.0016***	(0.0001)	-0.0017***	(0.0002)
ReviewSentiment	0.567***	(0.0326)	0.579***	(0.0373)	0.586***	(0.0431)
PastReviews	-0.0016***	(0.0003)	-0.0018***	(0.0003)	-0.0018***	(0.0004)
Review environment for hotel *j* until time *t*[6]						
ReviewRating	0.459***	(0.0335)	0.363***	(0.0432)	0.313***	(0.0541)
Hotel *j*'s OMR characteristics until *t*						
OMRVolume	0.00029*	(0.0001)	-0.00022	(0.0002)	-0.00038*	(0.00015)
Acknowledgment	**-0.602*** **	(0.121)	**-0.433** **	(0.144)	**-0.373***	(0.190)
Account	0.180	(0.326)	0.230	(0.409)	0.0964	(0.348)
Action	**0.417*** **	(0.105)	**0.440*** **	(0.126)	**0.355***	(0.142)
Affect	-0.00643	(0.117)	0.00544	(0.134)	0.0481	(0.159)
Congruence	0.151	(0.161)	0.249	(0.214)	0.279	(0.245)
Hotel characteristics	Not controlled		Controlled		Controlled	
Variation of baseline positivity (negativity) of reviewer *i* for hotel *j*					0.0472**	(0.0177)
Number of observations	25258		18906		18906	
Log-likelihood	-15384.269		-11672.042		-11654.758	

We present standard errors in parentheses. Hotel characteristics included the number of amenities in the hotel, hotel size, hotel age, and hotel class. Note that the second and third models had a lower number of observations due to missing data in hotel characteristics.
∗p < 0.05; ∗∗p < 0.01; ∗∗∗p < 0.001; − p < 0.1.

5.2 Relationship between Management Responses and Hotel Revenue

Next, we investigated whether hotels experienced an increase in revenue with OMRs. We constructed a quarterly dataset that aggregated the reviews and responses for each hotel. We used a hotel (*i*) and quarter (*t*) combination as the unit of analysis: for hotel *i* that has been reviewed until quarter *t*, a hotel's revenue is given by:

$$\begin{aligned}\log(Revenue)_{i,t} &= \alpha_0 + \phi Review_{i,t-1} + \varphi OMR_{i,t-1} + \theta(HotelClass_i \times OMR_{i,t-1}) \\ &+ \eta_{1:n_4} HC_{i,t} + \tau_1 City_i + \tau_2 Quarter_t + \tau_3 (City_i \times Quarter_t) + u_{i,t}\end{aligned} \tag{2}$$

$Review_{i,t-1}$ is a vector of time-varying review environment characteristics of the hotel *i* before quarter *t*, which includes ReviewRating, ReviewVolume, and ReviewLength. $OMR_{i,t-1}$ is a vector of the cumulative OMR activities by hotel *i* before quarter *t*, such as the number of OMRs, AAAA extracted from OMRs, and the congruence between reviews and OMRs. To examine how the relationship between OMR and revenue varied by hotel class, we included the interaction terms between $HotelClass_i$ and $OMR_{i,t-1}$. $HC_{i,t}$ denotes a vector of hotel *i*'s characteristics at time *t*. We also included $City_i$, $Quarter_t$, and their interaction term to control for 1) city-specific, time-invariant differences, 2) factors that vary arbitrarily over time but do not vary across cities, and 3) city-specific economic trends during the time to account for the market impact on hotel revenues (Zervas, Proserpio, & Byers, 2017). $u_{i,t}$ denotes the error term.

[5] We can provide full estimation results on request.
[6] We dropped ReviewVolume of prior reviews to avoid multicollinearity with OMRVolume.

We fitted the regression model (Model 2) with the Heckman selection method (Heckman, 1979) by using full maximum likelihood to address a potential issue of selection bias in our estimation. For example, hotels responding online to consumer reviews could be endogenous. That is, the hotels that respond to reviews could care more about consumer satisfaction and, thus, pay more attention to improve their services, which could improve future revenues. Specifically, we assumed that $Revenue_{i,t}$ is observed given responding to reviews if

$$\omega_0 + \omega_1 ReviewRating_{i,t-1} + \omega_2 ReviewVolume_{i,t-1} + \omega_3 OMR_{i,t-1} + \omega_4 HC_{i,t} + \tau_{i,t} > 0$$

where $u_{i,t}$ and $\tau_{i,t}$ have a correlation ρ. In other words, this specification assumed that the hotels did not provide OMR randomly and made deliberate decisions regarding whether to respond to reviews or not. If we only included hotels that responded to reviews in the revenue model, the observed revenue sample could have contained upward bias because such responding hotels may care more about customer services. Hence, we used this Heckman correction procedure to correct for the potential bias from non-random OMR participation of hotels when we estimated the revenue model (Model 2).

We first report our results only with the review metrics and OMR metrics in the "Model 1" column in Table 7. We then performed stepwise regressions by incrementally adding interaction terms between OMR and hotel class. We show the results for full model in the "Model 3" column in Table 7.

Among the OMR-related variables of interest, acknowledgment, action, and affect had statistically significant main effect at $p < 0.1$ in the second and third models (see Table 7). These results initially demonstrate that different ways in which hotels respond to reviews have various effects on their revenue. The 0.954 coefficient for acknowledgement indicates that a one percent increase in the proportion of OMRs that included acknowledgement resulted in a 0.96 percent[7] increase in revenue. Because the average quarterly hotel revenue was US$13.79 million, such an increase brought an extra US$132,186 in quarterly revenue. Similarly, the 1.739 coefficient for action indicates that a one percent increase in the proportion of OMRs that offered action in the OMRs resulted in a 1.75 percent increase in revenue. Such an increase brought an extra US$241,906 in quarterly revenue. We found it surprising to see that positive or negative affect had a negative main effect. Therefore, we further investigated the effects of OMRs based on hotel class. We can see that the interaction terms for Model 2 and Model 3 in Table 7 had statistically significant effects at $p < 0.05$. For example, as we discuss above, OMRs can be effective in driving revenue if the OMRs include content that show managers' action to address issues in the reviews. However, the effect diminished when hotel class became high (the effect of *HotelClass* × *Action* was -0.500 at $p < 0.001$). Each star rating increase in Hotel Class decreased the abovementioned effect that action had on revenue by US$68,778 until it becomes insignificant when the Hotel Class exceeded three stars. This finding suggests that lowly-rated hotels may be better off by explicitly expressing their actions in their responding than highly rated hotels. To show the results more effectively, we graphically present the average marginal effects that the OMR content variables had on revenue by different hotel class in Figure 4.

The results in Figure 4 have important implications. They demonstrate that lower-tier hotels responding to online reviews in which they indicate they will improve quality either by acknowledgment or action could increase potential consumers' willingness to book with them. However, higher-tier hotels may deteriorate their revenue when they indicate quality improvement in their responses. We believe that such responses from higher-tier hotels may adversely and saliently confirm their service problems to consumers who have high expectations about service from those higher-tier hotels. Therefore, the problem echoed in the responses may make consumers less likely to book the higher-tier hotels that acknowledge issues and express they will improve quality.

[7] We calculated this number as follows: (exp(0.954/100) – 1) * 100

Table 7. Estimates of Management Responses on Revenue

	Heckman selection model		
DV: Log (*Revenue*) $_{t}$	Model 1	Model 2	Model 3
Rating metrics			
ReviewRating$_{t-1}$	**0.128****	**0.135****	**0.142****
	(0.0490)	(0.0484)	(0.0465)
ReviewVolume $_{t-1}$	**0.00213*****	**0.00228*****	**0.00239*****
	(0.000569)	(0.000560)	(0.000545)
ReviewLength $_{t-1}$			0.000154***
			(0.0000404)
Management response metrics			
OMRVolume $_{t-1}$	**-0.00413***	**-0.00391***	**-0.00460***
	(0.00202)	(0.00194)	(0.00189)
RespondTime $_{t-1}$	0.000143	**0.000391***	**0.000345***
	(0.000179)	(0.000180)	(0.000174)
Congruence $_{t-1}$	0.0139	**-1.609***	-1.084
	(0.125)	(0.701)	(0.690)
Acknowledgment $_{t-1}$	**0.209****	**0.615+**	**0.954****
	(0.0674)	(0.323)	(0.318)
Account $_{t-1}$	**0.478*****	-0.491	0.0180
	(0.136)	(0.531)	(0.523)
Action $_{t-1}$	0.117	**1.558*****	**1.739*****
	(0.0755)	(0.347)	(0.337)
PositiveAffect $_{t-1}$	-0.0328	**-1.312***	**-1.034+**
	(0.144)	(0.541)	(0.528)
NegativeAffect $_{t-1}$	-0.0863	**-0.757+**	**-1.046***
	(0.0852)	(0.417)	(0.408)
HotelClass × Congruence $_{t-1}$		**0.574***	**0.467***
		(0.228)	(0.224)
HotelClass × Acknowledgment $_{t-1}$		-0.144	**-0.228***
		(0.104)	(0.102)
HotelClass × Account $_{t-1}$		**0.310+**	0.160
		(0.179)	(0.176)
HotelClass × Action $_{t-1}$		**-0.492*****	**-0.500*****
		(0.112)	(0.108)
HotelClass × PositiveAffect $_{t-1}$		**0.453****	**0.386***
		(0.160)	(0.156)
HotelClass × NegativeAffect $_{t-1}$		0.228	**0.326***
		(0.139)	(0.135)
ResponseLength $_{t-1}$			-0.000458***
			(0.0000932)
Hotel and market controls[8]			
Hotel-related controls (hotel class, age, size, and amenities) are included.			
Time, location and time × location (market trend) are included.			
Number of observations (censored/uncensored)	414	414	414
Log-likelihood	-1003.01	-985.0135	-969.3824
Standard errors in parentheses, + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.			

[8] We can provide full estimation results on request.

On the other hand, higher-tier hotels usually benefitted from responding to reviews when their response content related to congruence, account, and affect as the upward slopes in Figure 4 show. For the congruence between the review and response, when higher-tier hotels discussed the issues that responses raised, their potential consumers were more likely to book them in the future. In contrast, repeating the exact issues in the responses may be meaningless or even harmful to lower-tier hotels. Similarly, providing a justification or explanation to raised issues may increase consumers' willingness to book higher-tier hotels. Although account and its interaction term with hotel class did not have a significant effect on revenue on average (see Table 7), Figure 4 shows that, at the individual hotel class level, account was positively and significantly associated with revenue when the hotel class exceeded 2.5. However, such behavior lacked importance or even harmed lower-tier hotels. We also found this pattern with affect in the response, which may indicate that, for potential lower-tier hotel consumers, the actual action is more critical than the explanation and tune, whereas higher-tier hotel consumers may care more about responses' attitude than the actual action.

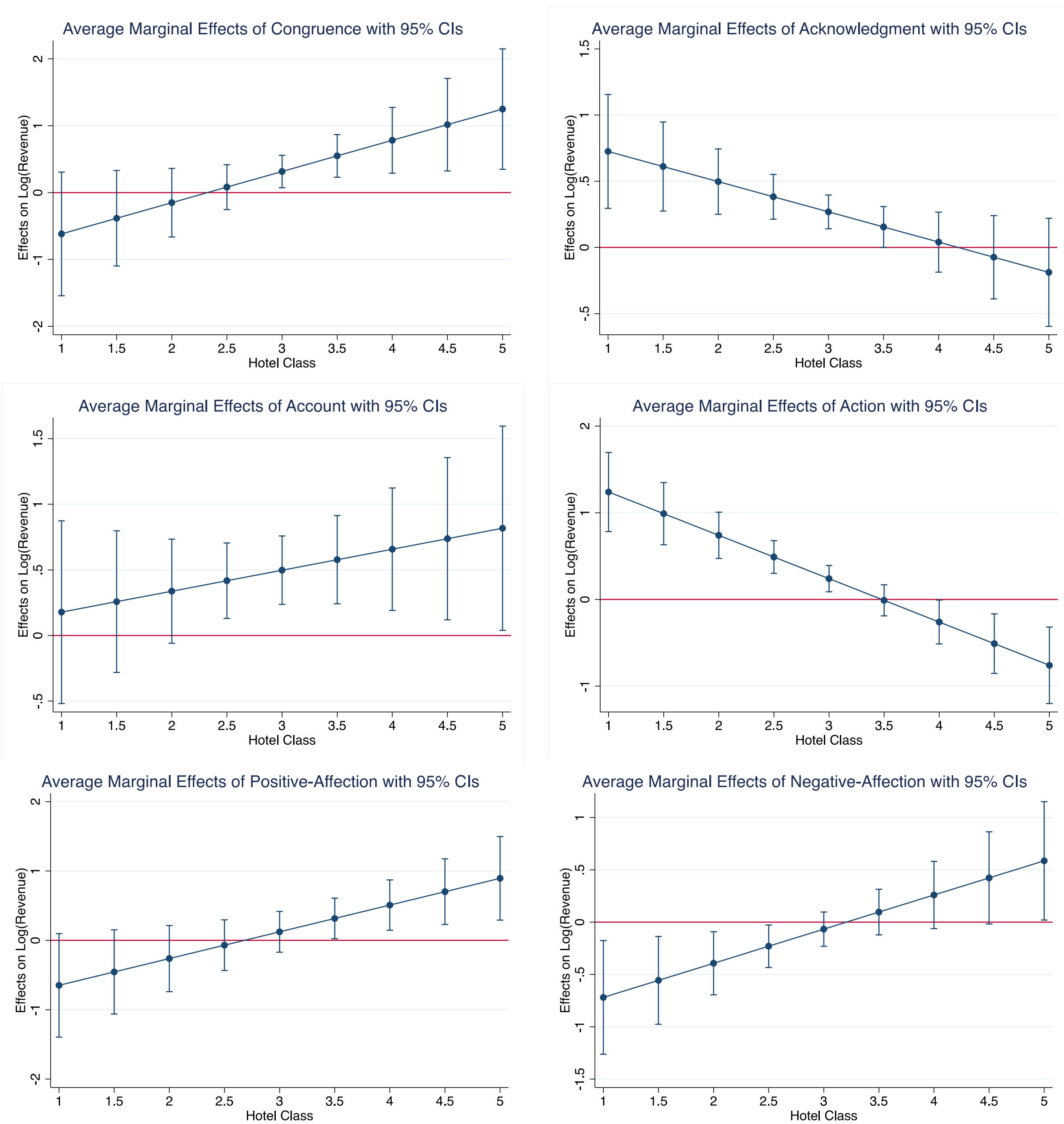

Figure 4. Average Marginal Effects of OMR Content Variables on Log(Revenue) by Hotel Class

6 Discussion and Implications

While managerial interventions play an increasingly important role in online review platforms, in this study, we demystify the role that managerial responses play in improving firm performance by empirically achieving two important research goals. First, we designed a framework that quantifies managerial responses based on their sentiment and semantic characteristics. Second, we evaluated this framework and investigated the relationship between managerial response strategies and business performance. We expand on each goal below.

First, we developed an action-driven framework to classify response strategies that add to the management response literature. Our theory-driven text-mining framework offers specific and effective management response strategies based on reviews' content and sentiment. This framework offers scholars a more comprehensive way to measure OMRs' effectiveness. This framework also serves as a toolkit that one can use not only to extract a given response's semantic and sentiment aspects but also to quantify the linguistic alignment between a response and the review it addresses. Scholars with an interest in classifying textual reviews can adopt and possibly extend it.

Second, we used the AAAA framework to empirically investigate how managers can strategically leverage their online responses' content and sentiment so as to maximize the positive impact that WOM can have on their business. Specifically, we found that managerial responses influence consumer satisfaction and revenue in different ways. On the one hand, we found action in a response to be positively associated with future consumer satisfaction but acknowledgment to be negatively associated with future consumer satisfaction. Affect, action, and congruence exhibited no significant relationship with future consumer satisfaction. On the other hand, all AAAA variables (i.e., acknowledgment, account, action, affect) and congruence significantly related to firms' financial performance depending on and moderated by hotel class.

Specifically, while acknowledgment in responses may lower subsequent consumers' ratings, it can lift a hotel's sales in the long term for lower-tier hotels. This finding shows that consumers' post-purchase evaluation behavior does not necessarily align with their purchase behavior, especially for lower-tier hotel consumers. Potential consumers might appreciate the acknowledgment in prior responses and, thus, decide to choose the hotel. However, after individuals experience certain problems during their stay, such acknowledgment might reinforce the negative experience and, thus, negatively impacting their evaluation. The positive relationship between acknowledging the problems and future revenue deteriorates or even becomes insignificant when higher-tier hotels offer acknowledgement. Such an affect results from the disappointment that consumers perceive when they observe a mismatch between their high expectations of higher-end hotels and the acknowledgements from management about its negative service quality. Therefore, higher-tier hotels should avoid acknowledging the issues in the response to maintain their sales and avoid a decrease in their future ratings.

We also observed a positive relationship between action and the subsequent consumer ratings for future revenue but only for lower-tier hotels. Offering action can even hurt future revenue for higher-end classes, and this harmful effect increases when the hotel class increases. Therefore, lower-tier hotels should focus on providing a plan to improve their service to increase both future ratings and revenue, but higher-tier hotels should avoid it if they want to improve their sales in the long run.

Finally, although we found that affect, account, and congruence did not play a role in increasing future ratings, they positively related to future revenue for higher-tier hotels. Therefore, lower-tier hotels should focus on acknowledging the problem and offering to remediate it. Managers in higher-tier hotels, however, should instead focus on offering an explanation in the responses and try to be as specific as possible when they offer such explanations. Interestingly, we note that OMRs related to consumers' purchase behavior and post-purchase evaluation behavior in different ways. As we hypothesized earlier, one reason could be that consumers appreciate hotels acknowledging problems and offering future actions when they make the purchase decision. However, they get disappointed when they stay at the hotel and realize that a hotel did not actually address the problems. Therefore, future studies should investigate whether hotels actually address the issues that prior consumers raise or not (Ananthakrishnan et al., 2019).

These findings provide important theoretical implications. By empirically evaluating our framework's effectiveness, we show that OMRs can influence not only consumers' subsequent satisfaction but also firms' financial performance. Our findings add to the research stream on how OMRs affect customer satisfaction and business performance (e.g., Chen et al., 2019; Chevalier et al., 2018; Gu & Ye, 2014; Kim et al., 2015; Kumar, Qiu, & Kumar, 2018a; Proserpio & Zervas, 2017; Wang & Chaudhry, 2018; Xie et al., 2017, 2014, 2016) by showing how different OMR aspects relate to future ratings and revenue in different ways. Our findings show that the content in managers' responses rather than the frequency with which managers respond contributes to consumers' perceptions (e.g., Wang & Chaudhry, 2018). Improving consumers' satisfaction and outperforming the market is relevant and valuable to a business. With assistance from our framework, firms can strategize their responses to online reviews more effectively. Therefore, by investigating the relationship between online managerial responses and future consumers' attitudes and the relationship between such responses and hotels' financial performance, we demonstrate the relevance of the business problem that our framework can assist in addressing.

Our findings also have important practical implications. First, the AAAA framework offers companies a device to evaluate the quality of their managers' responses quantitatively. Such qualities include the affection in the responses and the extent to which the topics in the responses assemble the topics in the reviews. Second, our findings reveal valuable insights to assist managers in strategically developing their responses to increase financial performance. When responding to reviews, since the time delay between review and response does not play a significant role in sales, managers should not rush but carefully compose their responses. We found that responses that express acknowledgment and action have more value than responses that express other content. A one percent increase in responses that include either acknowledgement or action content will generate extra quarterly revenue of about US$0.13 million and US$0.24 million, respectively. When responding to reviews, managers may want to focus on these two aspects because they carry more monetary implications to their businesses than other contents. Finally, managers should consider adopting different strategies when responding to reviews based on the hotel class they work for. While acknowledgment and action have a positive monetary impact on revenue, the effect decreases by about US$30,000 and about US$68,000, respectively, with every star rating increase in hotel class and eventually becomes insignificant. On the other hand, the effect that account has on revenue increases when hotels have a higher star rating. Therefore, managers in lower-tier hotels should prioritize their effort to acknowledge the problem and offer a solution in their responses, while managers in high-end hotels should provide explanations to the specific problem. Thus, managers for hotels at different levels can use our findings to assess the financial returns of responding to reviews.

7 Concluding Remarks

In this study, we develop a text analytical framework to classify managerial responses to online reviews. We then demonstrate the framework's relevance and applicability by empirically applying it to a dataset that contains 37,896 managerial responses to online reviews for 390 hotels. Our results confirm that managers can improve both their hotels' reputation and financial performance by following this framework when responding to online reviews and should look to incorporate such a systematic approach when responding to online inquiries. We also conclude that managers should not neglect response to positive reviews as responding to positive reviews can play a significant role in promoting brand loyalty and lead consumers to perceive the business better overall.

We note that our study has several limitations. First, we evaluated whether and the extent to which OMRs affect subsequent consumer ratings and hotel revenue. However, these two outcomes can depend on other factors in addition to OMRS, such as advertisement spending and personal stay experience. However, we did not focus on building models to predict ratings and revenues; rather, we used such estimation to demonstrate and evaluate our text analytics framework's effectiveness. Researchers and practitioners can adapt this framework to quantify other content-related managerial response features that pertain to their research and business problems. Second, although we developed our list of hotel review topics via a rich set of methods such as text link analysis, clustering analysis, and linguistic-based methods, the topic list does not exhaustively include all topics. We encourage other researchers who conduct work in this field to explore, advance, and extend the methods that we employed. More specifically, it would be interesting to evaluate the best fitness of other advanced predictive models that exploit the multilevel structure of social media platform data like ours. Third, in this study, we collected and analyzed responses only from a single platform. However, businesses typically use multiple channels when responding to online reviews. Focusing on one platform may limit the research's scope and may not appropriately capture all intricacies that online WOM involves. In the future, researchers could investigate how managers use different channels to respond to reviews. By doing so, they could address potential endogeneity issues between response and hotel performance. Researchers could also investigate how the effects that OMRs have on hotels' future ratings and revenue may change over time. For example, when more and more businesses understand the value that they can generate by responding to online reviews and using such responses effectively, consumers may start to expect to always receive responses by default. Such expectations may result in changes in how OMRs can influence purchase and evaluation behavior. That said, we hope that, by revealing how managerial responses to online reviews can improve firm performance, we convey the great potential of scholarly work in this exciting area. Accordingly, we call for future work that continues to theoretically and empirically explore it.

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Appendix

Table A1. Example Descriptors and Topics Revealed by Different Text Mining Techniques

Technique	Example descriptor	Topic(s)
Text link analysis	"location" + "close"	Positive location
Clustering analysis	"excellent", "hotel", "stay", "room", "clean", "good", "friendly", "river walk"	Multiple topics*
Frequent term	"quiet"	Positive quietness
Regular expression rule	["smell "& (<Negative>** | <NegativeFeeling> | <Contextual>) & !("no")]	Negative cleanliness

*: Terms in this example belong to the same cluster because they appeared together frequently. They reflected positive topics that the reviews mentioned. We added terms in this cluster to multiple topics (positive service, positive room, positive cleanliness, etc.)
**: <Negative> denotes the "negative" keyword group, which included 2,979 keywords such as "not sufficient", "bad", and "awful".

Table A2. Illustrative Example of Linguistic-based Methods[9]

Method	Mechanism	Original descriptor	Descriptors added	Topic(s)
Concept inclusion	Starts with a term and identify all the terms that include it	"quiet"	"quietness"	Positive quietness
Semantic networks	Extends descriptors by identifying synonyms and hyponyms	"downtown"+ "not close to"	"long way from downtown", "closer to downtown", "not right downtown"	Negative location
Concept derivation	Groups terms by looking at the endings of each component in a term and finding other terms that have corresponding components with a related ending.	"not responsive"	"staff not responsive"	Negative service

Table A3. The Topic Modeling Algorithm

Topic modeling algorithm

Input: A large corpus *C*, a predefined topic set *T*
Output: (1) an extended topic set *T;* (2) a descriptor set *D* (a collection of Descriptor sets D_i for each topic T_i in *T)*
Perform **Keyword Extraction**, **Text Link Analysis,** and **Clustering Analysis** to *C*
While new patterns emerge **or** keywords not assigned to *D*
if keyword/text link patter/cluster *k* is appropriate to describe T*j* in T:
Assign *k* to *Dj*
else
Add new topic T_{j+1} to *T*
Assign *k* to D_{j+1}
End while
For D_j in *D*
Perform **Descriptor Set Extension**

[9] Please refer to IBM's SPSS Modeler text analytics user guide (link below) for more information: ftp://public.dhe.ibm.com/software/analytics/spss/documentation/modeler/18.0/en/ModelerTextAnalytics.pdf

Table A4. The Hotel Review Topics and Examples

Review topics and number of reviews*	Example descriptors	Example review
Positive room (54928 reviews)	[<Room> + <PositiveFeeling>] [<Room> + <Positive>] [<Room> + <PositiveFunctioning>]	*The room itself was exceptionally clean and it appeared evident that a face-lift had taken place relatively recently. The linens appeared new(er) and the couch and other furniture did not have the trademark tells of having a number of guests pass through recently.*
Negative room (25504 reviews)	[<Room> + <NegativeFeeling>] [<Room> + <Negative>] [<Room> + <NegativeFunctioning>]	*Bugs, dirt, and mold all over the room. A 2 bed room with 1 towel and 1 wash cloth. And they were stained…* *Some rooms, according to other guests, were either way too hot, or just below freezing…*
Positive personnel (50134 reviews)	[<Personnel> + <PositiveCompetence>] [<Personnel> + <PositiveAttitude>]	*I was pleasantly surprised with very helpful staff—they went over and above board to make my stay comfortable. I had initial problems connecting to the wireless network on my laptop—the lovely young lady from the front desk came down and worked about 15 minutes to help me get online. I apologized for the inconvenience and she smiled and said she was glad to help.*
Negative personnel (7566 reviews)	[<Personnel> + <NegativeCompetence>] [<Personnel> + <NegativeAttitude>]	*The lady on reception is exactly as everyone else describes and is rude, unhelpful and makes you feel like a complete inconvenience.*
Positive cleanliness (36648 reviews)	Tidy, clean, spotless	*The rooms were very clean (don't forget to tip your housekeepers!)*
Negative cleanliness (6708 reviews)	Dirty, disgusting, filthy	*Very disgusting! Walls, showers, floors, doors, pool. just disgusting! Bugs in the bathroom. I cant stress enough just how filthy this place is. I couldnt even sit my bags down in the room. I stayed for twenty minutes and got my money back.*
Positive amenity (35183 reviews)	[<HotelAmenities> + <PositiveFunctioning>] [<HotelAmenities> + <PositiveFeeling>]	*This Residence Inn is in a perfect location and closest lodging to the Cultural District west of downtown Fort Worth. It is about one year old, in excellent condition, clean, odor-free, and has every amenity you could ask for, including heated pool and hot tub, hair dryer, fully-equipped kitchen, exercise room, thick towels, good water pressure, free newspapers and a shuttle service that will take you anywhere within a four mile radius and pick you up again…*
Negative amenity (3387 reviews)	[<HotelAmenities> + <NegativeFunctioning>] [<HotelAmenities> + <NegativeFeeling>]	*The elevator is broken, the pool is broken, the wifi didn't work, most of the things they advertise are straight up not true….*
Positive restaurant (27011 reviews)	[<Food> + <Positive>] [<Restaurant> + < Positive >]	*The breakfast was always fresh and hot. I would definitely consider staying here again when visiting Fort Worth.*
Negative restaurant (4328 reviews)	[<Food> + <Negative>] [<Restaurant> + <Negative>]	*Breakfast consisted of old apples, stale muffins and humidified cereal. Good thing they had coffee and milk, at least.*
Positive location (24724 reviews)	[<Location> + <Positive>] Close proximity [area + safe] [attractions + close to] [location + convenient]	*The location is great. Across from the convention center, close to most everything so restaurants are an easy walk...*

Negative location (563 reviews)	[neighborhood + bad] [location + would be good] [location + bad] [downtown + not close to]	*But I do have a couple of complains. 1) It is located next to the expressway, so you can hear trucks and motorcycles.*
Positive budget (18001 reviews)	[<Budget> + <Positive>] <PositiveBudget>	*With hotel prices soaring in west Fort Worth, I was happy to locate this property to affordably book two rooms for four nights.*
Negative budget (11675 reviews)	[<Budget> + <Negative>] <NegativeBudget>	*CheapOStay did agree to refund some of my money but charged me $68.00 for a filthy unsafe room that I did not even say at.*
Positive recommendation (16801 reviews)	<PositiveRecommendation>	*I will definitely go back and recommend others to this hotel.*
Negative recommendation (6702 reviews)	<NegativeRecommendation>	*I would not stay at this ever again at any price.*
Positive service (14214 reviews)	[<Services> + <PositiveCompetence>] [<Services> + <Positive>] [<CheckInOut> + <PositiveCompetence>]	*Excellent service and they will make you feel right at home. Two big thumbs up!!*
Negative service (4596 reviews)	[<Services> + <NegativeCompetence>] [<Services> + <Negative>] [<CheckInOut> + <NegativeCompetence>]	*This is the worst hotel I have ever stayed in!!!! Customer service was horrible…*
Positive quietness (9730 reviews)	Quiet	*I was given a room on the top floor, it was very quiet, even when there was live music playing…*
Negative quietness (609 reviews)	Noisy, loud	*The air conditioning was a bit noisy but we could stop it during the night (cool nights in end September).*
Positive experience (3851 reviews)	[<Experience> + <Positive>]	*The rooms were huge and clean and was equipped with essential appliances like microwave, fridge. Overall, my experience at this hotel was awesome.*
Negative experience (1122 reviews)	[<Experience> + <Negative>]	*A very very bad experience. Use at your own risk.*
Positive view (3245 reviews)	[<View> + <Positive>] riverview	*The room was uneventful in its appearance, but it did have a great view of Main St. and downtown Fort Worth from the 16th floor balcony/terrace.*
Negative view (436 reviews)	[<View> + <Negative>]	*We were on the ninth floor and still had a horrible view…*
Positive internet (1744 reviews)	[<Internet> + <PositiveFunctioning>]	*It is great hotel. very comfortable location It is very close to my Business. Great staff particular Manager. Great wireless and wired internet…*
Negative Internet (1265 reviews)	[<Internet> + <NegativeFunctioning>]	*I had initial problems connecting to the wireless network on my laptop - the lovely young lady from the front desk came down and worked about 15 minutes to help me get online.*
Positive sleep (749 reviews)	[<Sleep> + <Positive>]	*Big TV, Wireless internet, good night's sleep.*
Negative sleep (769 reviews)	[<Sleep> + <Negative>] Sleepless night	*If I hadn't been desperate for a place to stay at 2:00am I would have checked out as soon as I walked in!!! I didn't sleep much because I kept jumping out of bed because I kept feeling things crawling on me. I checked in at about 2am and I set my alarm for 5:00am to get the hell out of there!! I didn't even go anywhere eles in the motel, I was too scared to find out what eles I might see at the Motel Hell! DONT STAY HERE!!!* *The rooms were adequate but the pillows were*

		at most 1 inch thick and sleeping was tortured.
*Out of all 98,371 reviews		

Table A5. The AAAA Categories with Definition and Examples

AAAA categories	Top two subcategories	Definition	Examples
Acknowledgment (33853 out of 37896 documents categorized) **Subcategories**: appreciation, apology, admission, accept responsibility, dispute	Appreciation (32457 documents)	Gratitude offered to reviewer for providing relevant feedback.	*Thank you for staying with us this past weekend and for taking time to review your stay with us. I appreciate your comments.*
	Apology (4959 documents)	Say sorry/express regret.	*We sincerely apologize for your unpleasant stay.*
Account (887 out of 37896 documents categorized) **Subcategories**: excuse, justification, reframing, refusal	Justification (647 documents)	The rationalization that the responder offers to the reviewer to establish the incident in a context to which the reviewer can relate or otherwise find reasonable.	*We have made many property renovations and we understand that it is never a good time to be under construction, but it is necessary in order to stay current and provide the best possible amenities for our guest.*
	Excuse (255 documents)	An explanation in which the responder admits that the problem raised is appropriate but denies full responsibility by citing external causes or uncontrollable circumstances (e.g., "act of God").	*I am so sorry that you had such a bad experience with being in a room by the elevator. Unfortunately, due to the nature of our hotel, there are rooms near elevators.*
Action (6767 out of 37896 documents categorized) **Subcategories**: contact, investigation, financial action, promise, rectify, invite back)	Invite back (3204 documents)	An invitation to the reviewer to come back to the hotel.	*I want to thank you for taking the time to post a review of your stay. Thank you again for posting your review. We look forward to having you visit with us again in the future.*
	Contact (1946 documents)	An invitation to the reviewer to contact the hotel staff to further discuss the problem or/and reach an agreement on solution.	*Please kindly contact our Guest Relations department so they can have a record of your experience to help us provide you and our other guests with better service in the future.*
Affect (7311 out of 37896 documents categorized) **Subcategories**: negative affect includes shame, embarrassment, regret, worry, and disappointment Positive affect includes happiness, contentment, excitement, and pleasure	Negative affect (5079 documents)	Negative emotions that a responder expresses due to underlying circumstance such as shame, embarrassment, regret, worry, and disappointment.	*We are pleased that you selected our property, yet truly disappointed that your room type of choice was not honored.*
	Positive affect (2531 documents)	Positive emotions that a responder expresses due to underlying circumstance such as such as happiness, contentment, excitement, and pleasure	*Your review was a pleasure to read.*

Table A6. Percentage of Responses to Reviews by AAAA Topic

AAAA Topic	Percentage of responses
Acknowledgment	**89.33%**
Appreciation	85.65%
Apologize	13.09%
Admission	5.08%
Accept responsibility	0.81%
Dispute	0.01%
Account	**2.34%**
Justification	1.71%
Excuse	0.67%
Reframe	0.00%
Denial	0.01%
Action	**17.86%**
Contact	5.14%
Financial compensation	0.30%
Investigation	0.08%
Invite Back	8.45%
Promise of future action	0.55%
Rectify	5.06%
Affect	**19.29%**
Negative (shame, embarrassment, regret, worry, and disappointment)	13.40%
Positive (happiness, contentment, excitement, and pleasure)	6.68%

Table A7. Correlation Matrix of Variables in the Review-level Dataset

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1) Rating	-																
2) LocationRating	0.56	-															
3) CleanlinessRating	0.78	0.53	-														
4) ServiceRating	0.80	0.48	0.67	-													
5) SleepQualityRating	0.76	0.50	0.71	0.64	-												
6) ValueRating	0.81	0.50	0.68	0.71	0.70	-											
7) ReviewLength	-0.26	-0.11	-0.19	-0.24	-0.20	-0.21	-										
8) ReviewSentiment	0.62	0.37	0.55	0.57	0.53	0.56	-0.15	-									
9) PastReviews	-0.04	-0.04	-0.02	-0.01	-0.03	-0.05	0.12	0.03	-								
10) ReviewVolume	0.12	0.17	0.13	0.11	0.10	0.04	-0.08	0.04	-0.06	-							
11) ReviewRating	0.34	0.23	0.33	0.29	0.28	0.26	-0.12	0.23	-0.02	0.31	-						
12) OMRVolume	0.12	0.17	0.13	0.10	0.10	0.04	-0.08	0.04	-0.06	1.00	0.31	-					
13) Acknowledgment	0.02	0.04	0.02	0.02	0.02	0.02	-0.02	0.03	0.02	-0.06	0.10	-0.06	-				
14) Account	-0.04	-0.02	-0.03	-0.03	-0.05	-0.04	0.07	-0.02	0.04	-0.07	-0.13	-0.07	0.04	-			
15) Action	-0.09	-0.10	-0.10	-0.08	-0.09	-0.06	0.03	-0.07	0.00	-0.21	-0.25	-0.20	0.02	0.18	-		
16) PositiveAffect	-0.17	-0.10	-0.16	-0.15	-0.14	-0.14	0.05	-0.11	0.01	-0.20	-0.50	-0.20	0.17	0.12	0.16	-	
17) NegativeAffect	-0.01	0.00	-0.04	-0.02	-0.02	0.01	0.01	0.00	0.00	-0.12	0.00	-0.12	0.04	-0.04	0.17	0.11	
18) Congruence	0.02	0.00	0.01	0.02	0.01	0.02	-0.02	0.01	-0.02	0.01	0.05	0.01	0.14	0.12	0.19	0.08	0.07

Table A8. Correlation Matrix of Variables in the Hotel Quarter-level Dataset

	1	2	3	4	5	6	7	8	9	10	11	12	13
19) Log(REVENUE)													
20) ReviewRating	0.13												
21) ReviewVolume	0.50	0.20											
22) ReviewLength	0.15	0.02	0.05										
23) OMRVolume	0.19	0.02	0.46	-0.08									
24) RespondTime	-0.19	-0.03	-0.21	-0.03	-0.04								
25) Congruence	0.18	0.00	0.00	-0.04	0.01	0.12							
26) Acknowledgment	0.16	0.06	0.13	-0.01	0.18	-0.25	-0.03						
27) Account	0.08	0.16	0.16	-0.05	-0.08	-0.10	-0.05	0.17					
28) Action	0.09	-0.03	0.12	-0.10	-0.11	0.03	0.03	-0.37	0.02				
29) PositiveAffect	0.02	-0.05	-0.12	0.02	-0.01	0.08	-0.05	0.06	0.17	-0.06			
30) NegativeAffect	0.05	0.15	0.15	0.10	-0.09	-0.16	-0.08	0.32	0.37	0.04	-0.10		
31) ResponseLength	0.06	0.10	0.20	0.13	-0.09	-0.12	0.23	0.14	0.30	0.29	0.04	0.22	
32) HotelClass	0.76	0.27	0.44	0.16	0.20	-0.21	0.10	0.09	-0.07	-0.05	-0.07	0.03	-0.02

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