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경영학석사 학위논문

The Effects of Managerial Responses to Positive Reviews on Online Reputation

긍정 리뷰에 관한 관리자 응답이 온라인 평판에 미치는 영향

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The Effects of Managerial Responses to Positive Reviews on Online Reputation

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Abstract

While managerial responses to positive reviews are observed and

even encouraged in practice, there is little research on how and why

managerial responses to positive reviews are effective means for

reputation management. The study aims to provide a rich understanding

of this topic. Specifically, we investigate if managerial responses to

positive reviews are associated with higher review volume and valence.

Then, we test if and how the content characteristics of positive responses

affect future review volume and valence. We collected 60,916 reviews

from 2,214 restaurants located in New York from Trip Advisor, ranging

from Jan 1st, 2018 to Sep 19th, 2022. The analysis indicates that when

positive reviews are responded to, there is a 0.32-star increase in review

ratings. The results show that emphasizing the resourcefulness of a

business is the main driver for increasing future review ratings.

Keyword : Managerial Response, Positive Reviews, Online Reputation

Management, Trip Advisor, Natural Language Processing

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1. Research Motivation

In recent years, businesses have developed several effective online reputation management tactics. The tactics for online reputation management include incentivizing reviewers to give the highest rating, leaving negative reviews on competitors' business, and responding to customer reviews. Since online ratings are highly skewed these days, businesses have put more effort in generating high-quality, informative reviews in addition to receiving high rating from customers.

In this study, we focus on how to respond to customer reviews effectively. Specifically, we study effective response strategy to positive reviews. In the past, businesses focused mostly on responding to negative reviews because negative reviews are often seen as customer complaints that need to be handled professionally. However, more and more businesses respond to positive reviews. Platforms also encourage businesses to respond to customer reviews whether they are positive or negative. Figure 1 shows a sample managerial response to positive review on Trip Advisor.

We assume that response contents to customer reviews can differentiate a focal business from competitors. Companies can give additional product information or leave a positive impression with humor and kindness to buyers and potential customers. If a business owner responds to every positive comments, she has more chance to promote her business and win customer over. Under highly skewed review rating environment, there are more chances to promote a business via response sections to positive reviews than to negative reviews.

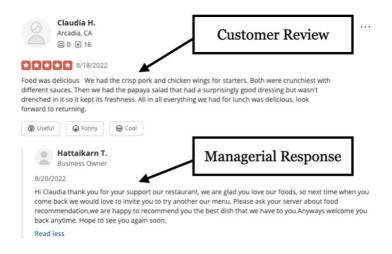


Figure 1. Sample Managerial Response to Customer Review on Trip Advisor

While managerial responses to positive reviews are considered essential and effective in practice, relevant research in information systems, marketing, and economics heavily centers around the effect of managerial response to negative reviews. Dealing with unsatisfied customers is important and minimize the risk of losing customers. However, highlighting positive aspects of a product or service described in reviews and signaling the quality of the business via response could also maximize a chance to win customers over. With this motivation, we investigate the effect of managerial responses to reviews, especially focusing on positive reviews in this study. Specifically, we answer two questions below.

RQ1. Do managerial responses to positive reviews increase future review valence and volume?

RQ2. What content characteristics of a positive response

increase future review valence and volume?

We approach the research questions with a crawled dataset of restaurants from Trip Advisor. First, we investigate if a response to positive reviews has a positive relationship with future reputation. Then, we extent our analysis to see how positive reviews can drive better reputation by analyzing the content characteristics of responses with natural language processing (NLP).

2. Literature Review

2-1. Impact of Managerial Responses to Positive Reviews

Existing research on the effects of managerial responses to online reviews studied whether managers' responses to reviews have a positive impact on future review valence and volume (Chen et al. 2019; Gu and Ye 2014; Ma et al. 2015; Proserpio and Zervas 2017; Ravichandran and Deng 2022; Wang and Chaudhry 2018). Ravichandran and Deng (2022) show that responding to reviews generally has a positive influence on future review valence. Chen et al. (2019) show that managerial responses increase the subsequent review volume. Proserpio and Zervas (2017) report a 0.12-star increase in ratings and a 12% increase in review volume when managers respond to online reviews. Table 1 summarizes prior literature on the research stream.

Although past studies have reported the overall positive impact of managerial responses, the distinct effect of managerial responses to positive reviews is conflicting. Ravichandran and Deng (2022) find that responses to negative reviews impact future review valence positively, while responses to positive reviews do not influence future review valence. On the other hand, Wang and Chaudhry (2018) find that a managerial response to positive reviews have a negative impact, while a response to negative reviews positively impacts future valence. Past research reports that the individual effect of managerial responses to negative reviews is positive. However, the individual effect of managerial response to positive reviews needs further investigation.

We think that there are several reasons why study on managerial responses to positive reviews is limited. First, responding to positive reviews

is the recent online management tactics by business owners. As most review platforms are at maturity stage, platform and business owners are coming up with new ways to manage online reputation and responding to positive reviews is one of those ways.

Second, although there is real-world evidence that more and more businesses are responding to positive reviews, it is hard to measure the effects of managerial responses to positive reviews econometrically. There are a lot more covariates and interactions terms to consider to achieve causal inference, such as business level covariates (restaurant quality, size), time level covariates(year, seasonal, COVID effect), review level covariates (length, sentiment), and response level covariates (length, sentiment, template). To overcome such statistical challenges, we considered conducting crossplatform comparison to extend our analysis to causal inference. However, we could not access to one of two representative restaurant review platforms in North America with a python scraper, which leads to our third point. Limited data access to text data of managerial response do not permit researchers to measure the managerial responses to positive reviews.

Literature	MR	MR-P	MR-N	Context	Dependent Variables	Methodology
Ravichandran and Deng (2022)	Positive Impact	ı	Positive Impact	Hotel Review	Review Valence	Panel Analysis
Chen et al. (2019)	Positive Impact	Positive Impact	Positive Impact	Hotel Review	Review Volume	ada
Kumar et al. (2018)	Positive Impact	ı	ı	Restaurant Review	Restaurant Performance	DD
Wang and Chaudhry (2018)	Positive Impact	Negative Impact	Positive Impact	Hotel Review	Review Valence	DD
Proserpio and Zervas (2017)	Positive Impact	ı	ı	Hotel Review	Review Volume, Valence	DD

Note 1: MR - Managerial Response, MR-P - Managerial Response to Positive Reviews, MR-N - Managerial Responses to Negative Reviews Note 2: We only included dependent variables that showed statistical significance in the corresponding literature

Table 1. Impact of Managerial Responses on Online Reputation Literature

2-2. Characteristics of Managerial Responses to Positive Reviews

Our study analyzes the content characteristics of managerial responses to investigate the mechanism behind the effect of managerial responses on online reputation. Past studies on this topic studied how response style affects future ratings. Response style includes length, sentiment, and timeliness of responses. Sheng et al. (2019) finds that when review ratings are increased, the response to previous reviews is longer, and the sentiment of the response is lower. While Wang and Chaudhry (2018) find that response timeliness to negative reviews is important, Sheng et al. (2019) find that timeliness does not influence review ratings. Unlike previous studies on the response style, out study classifies the response content characteristics and matches the content characteristics to the dimension of trust. We elaborate on this process more in the research design section. We included variables related to response style in our model as control variables.

3. Hypothesis Development

3-1. Trust in Electronic Commerce

We argue that managerial responses to positive reviews have a positive influence on future review valence and volume because they affect potential customers' trust. Following Ba and Pavlou (2002), we define trust in this study as a multidimensional concept consisting of (1) credibility and (2) benevolence. Trust means "the buyer's belief that a transaction with a seller will occur in a manner consistent with her expectation." Credibility is about a belief in a seller's competency and reliability, meaning that buyers can expect that the promised quality of service will be delivered. On the other hand, benevolence is a concept of good intention. A seller with benevolence is expected to act in goodwill, not opportunistically.

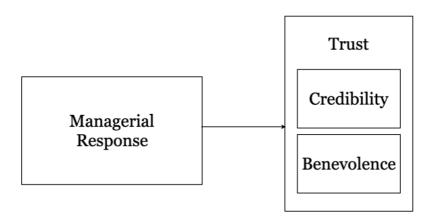


Figure 2. Conceptualization on the Impact of Managerial Responses on Potential Customers' Trust

Responding to positive reviews can signal a business' credibility and benevolence, increasing the trust of potential customers. For example, businesses can recommend what to try next time(credibility), thank customers for noticing its specialty(credibility), or show that their interaction is authentic by recalling specific characteristics of customers (benevolence). Hence, managerial response to positive reviews is likely to increase trust in potential buyers, affecting buying decisions positively. Our conceptualization is suggested in Figure 2. Thus, increased trust will be reflected in increased review volume and valence. Formally, we propose the following hypotheses:

- H1. Managerial responses to positive reviews will be associated with higher review volume.
- H2. Managerial responses to positive reviews will be associated with higher review valence.

Next, we investigate the mechanism behind the positive effect of managerial responses to positive reviews. With the elaboration likelihood model, we conceptualize how response content characteristics can affect two dimensions of trust.

3-2. Elaboration Likelihood Model (ELM)

ELM explains the persuasiveness of a message via two distinct routes (Petty and Cacioppo 1986). The central route occurs when message receivers' ability and motivation are high, and receivers understand the contents of a message at a cognitive level. Facts and arguments, such as comparing the product attributes, are important in the central route. On the other hand, the peripheral route is activated when the message receivers' ability and motivation are low. In the peripheral route, emotions or interactive cues are

important.

In the context of managerial response to positive reviews, a response including item recommendations and product attributes will be processed in the central route. Such information in a response would establish the expertise and professionalism of a business, affecting the credibility dimension of the trust. Conversely, a response that contains an emotional word or connects with a reviewer would be processed in a peripheral route. Such cues in a response would affect the benevolence dimension of trust because it reflects humbleness. In this paper, we refer to any cues that activate a central route as "informative cues." On the other hand, any cues that activate a peripheral route will be called "interactive cues." Hence, we conceptualize that informative cues in a managerial response affect credibility dimension of trust and that interactive cues in a managerial response affect benevolence dimension of trust. The visualization of our conceptualization is presented in Figure 3.

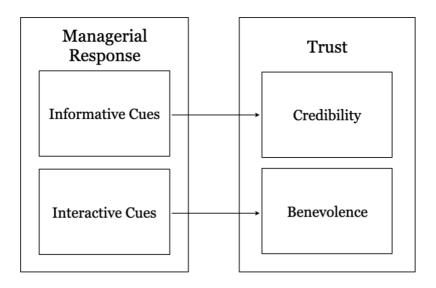


Figure 3. Conceptualization on How Content Characteristics of Managerial Responses Affect Trust of Potential Customers

We expect that the number of informative cues in a response to a positive review will have a positive relationship with review valence and volume. However, we do not expect the number of interactive cues will have a positive relationship with review valence and volume. Businesses have responded to reviews in interactive ways like a template, "Thank you John. We look forward to seeing you soon." It is rare to observe responses demonstrating business' competitive capabilities. Therefore, responses that demonstrate a business' professionalism and resourcefulness will be associated with higher review valence and volume. On the other hand, the number of interactive cues in a response to a positive review will not have any relationship with review valence and volume because it does not differentiate a business from other competitors. Formally, we propose the following hypotheses.

- H3. The number of informative cues in a managerial response will be associated with higher review volume.
- H4. The number of informative cues in a managerial response will be associated with higher review valence.
- H5. The number of interactive cues in a managerial response will not be associated with higher review volume.
- H6. The number of interactive cues in a managerial response will not be associated with higher review valence.

4. Research Design

4-1. Data and Variables

We collected 60,916 reviews from 2,214 restaurants located in New York from Trip Advisor with a python scraper. The data ranges from Jan 1^{st,} 2018 to Sep 19th, 2022. Initially, there were 9,493 restaurants listed on Trip Advisor on the data collection date. However, we only included the restaurants 1) that are claimed by the owners on Trip Advisor and 2) that have at least one review for the data analysis. The dataset includes a unique review ID, review rating, review title, review text, reviewed date, response content, response date for each review, and business ID.

With this dataset, we construct variables that are presented in Table 2. For dependent variables, we count the number of subsequent reviews received within 14 days after a focal review is posted (FutureReviewVolume). With this variable, we see if future review volume is associated with managerial responses to a positive review. Similarly, we test if the average ratings of the subsequent reviews that are posted within 14 days (FutureReviewValence) is increased. For independent variables, we construct binary variables, 1 if a review received a response, 0 otherwise (ResponsePos, ResponseNeg). Here, we intentionally did not assign reviews with 3-star ratings neither to ResponsePos nor to ResponseNeg. Previous literature included 3-star ratings as positive reviews (Chen et al. 2019; Ravichandran and Deng 2022). However, we observed that the sentiment of reviews with 3-stars rating in the dataset are generally negative. Hence, we included reviews with 4 or 5-star rating as positive reviews and reviews with 1 or 2 star-rating as negative reviews. As a result, we have 49,108 positive

reviews and 5,827 negative reviews. Among them, 5,744 positive reviews and 741 negative reviews were responded to. For control variables, we counted the number of words included in a response (*ResponseLen*) and the number of days taken for a response (*ResponseDelay*), referring to the previous literature.

Variable	Description
FutureReviewValence	The average ratings of the subsequent reviews
	that are posted within 14 days after a focal
	review are posted
Future Review Volume	The number of subsequent reviews that are
	posted within 14 days after a focal review is
	posted
ResponsePos	1 if a focal review rating from 4 to 5 received a
	managerial response, o otherwise
ResponseNeg	1 if a focal review rating from 1 to 2 received a
	managerial response, o otherwise
ResponseLen	The number of words included in a response
ResponseDelay	The number of days taken for a response

Table 2. Variable Descriptions and Summary Statistics

Variable	Min	Mean	S.D.	Max
FutureReviewValence	0	2.43	2.19	5
FutureReviewVolume	0	1.80	3.47	83
ResponsePos	0	0.09	0.29	1
ResponseNeg	0	0.01	0.11	1
ResponseLen	1	36.24	11.72	46
ResponseDelay	0	2.70	27.57	1330

Table 2. Variable Descriptions and Summary Statistics
(Continued)

4-2. Content-Tag Data and Natural Language Processing

The study aims to analyze the content characteristics of managerial responses to positive reviews and find the mechanism behind the effect of managerial responses to positive reviews on online reputation management. To assign the content characteristics of each review, we define a set of content tags, categorize the content tags either to informative cues or to interactive cues, and use natural language processing to attribute pre-defined content tags to 5,744 responses to positive reviews.

Step	Description
Step 1	Define a set of content tags guided by academic literature
	(Resnik and Stern, 1977) and industry guidelines (Yelp, Naver
	Smartplace)
Step 2	Categorize the content tags either to InformativeCues or to
	InteractiveCues
Step 3	Train eight n-gram language model classifiers and auto-tag
	responses to positive reviews
Step 4	Construct composite variables, InformativeCues and
	InteractiveCues
	Table 3. Content-Tagging Process

First, to define the content tags, we refer to prior literature on content categorization (Resnik and Stern 1977) and response guidelines by online review platform to sellers. For informative cues, content that highlights the restaurant's capability as a food service provider (*Expertise*) and emphasizes the operational excellence of a restaurant (*Resource*) can be included because it increases the credibility of a restaurant. Sharing a business goal (*Philosophy*) can also increase credibility because it gives the impression that

the restaurant operates in a systematic way. For interactive cues, we include tags that reflect an effort to build a relationship with customers: Including a reviewer' name in a response (NameCustomer), showing appreciation for leaving high rating or enjoying the meal (Appreciation), including emotional reaction about reviews (Emotion), addressing the specific issues raised in the review (Attentiveness), inviting reviewers back to restaurants (InviteBack). Content-tagging processes are summarized in Table 3 and the examples of responses and the corresponding content tags are presented in Table 4.

Sample Responses

Hi Stoup, thank you for sharing your feedback about your recent visit to Marta. I'm glad to hear that you enjoyed many dishes but sad to hear that the ones you liked the least were the pizzas. I wish I could have been around during your visit to help get you another pizza that was crispier. I will share your feedback with the culinary team. It is our goal to have all our guests leaving with the feeling that they were well taken care of and that they feel satisfied with the value of their meal and I'm sorry that you felt the opposite. As far as the wine list goes, we do have many options that are under \$100, I'm sorry if you were shown those options. Please let me know the next time you are coming back so that I can ensure you have a wonderful experience. Have a great day.

Dear Billy, How wonderful to read about your NYC experience and to be a part of your fun day! It was truly our privilege and pleasure to serve you and your wife a lovely meal. Thank you for your eloquent compliments for our lentil. And while I am glad you enjoyed it, I only wish you had been equally impressed with your DB Burger and

Content-Tags

{Philosophy,
NameCustomer,
Appreciation,
Emotion,
Attentiveness,
InviteBack}

{NameCustomer, Appreciation, Emotion, Attentiveness, InviteBack} hope on your next visit we can make sure everything is perfect for you. Your very gracious expression of your high esteem for Chef Daniel, as well as for db Bistro Moderne and our team, means a lot to us and we look forward to welcoming you and your wife again soon

Table 4. Examples of Managerial Responses to Reviews and the Corresponding Content Tags

Next, we manually attributed the defined eight content tags to fivehundred responses with two research assistants to create a train dataset. Three people (the author and two research assistants) manually tagged the responses, merged each classification result, and applied majority rule. If two or three people agree that a specific content tag belongs to a response, then the value of the tag for that response is one. After creating a train dataset, we trained n-gram model with the dataset. The classification problem did not require understanding the order of the words or the contexts. Therefore, we selected n-gram language models. Specifically, we vectorized the unstructured text data to bi-grams with TF-IDF vectorizer. Then, we employed a two-layer perceptron model, utilizing tensorflow module in python. We ran the algorithm to predict the defined content tags of the remaining 5,244 responses. After the classifier content-tagged each response, we constructed composite variables InformativeCues and InteractiveCues by summing up the value of the content tags. *InformativeCues* ranges from o to 3 and InteractiveCues ranges from o to 5. Content-tags description and summary statistics are summarized in Table 5.

Variable	Description		
InformativeCues	The number of informative cues in a sentence		
Expertise	1 if a message highlights the expertise in food,		
	o otherwise		
Resource	1 if a message highlights the resourcefulness of a		
	restaurant other than food, o otherwise		
Philosophy	1 if a message includes the goal of the restaurant,		
	o otherwise		
InteractiveCues	The number of interactive cues in a sentence		
NameCustomer	1 if a message includes a reviewer's ID or name,		
	o otherwise		
Appreciation	1 if a message includes thank you for focal review		
	rating from 1 to 2 received managerial response, o		
	otherwise		
Emotion	1 if a message includes emotional words such as		
	'happy', 'glad', and 'sad', o otherwise		
Attentiveness	1 if a message directly repeats or deals with the		
	specific issue in the review, o otherwise		
<i>InviteBack</i>	1 if a message includes the expectation of the next		
	visit, o otherwise		

Table 5. Content-Tag Descriptions and Summary Statistics

Variable	Min	Mean	Standard	Max
			Deviation	
InformativeCues	0	0.19	0.52	3
Expertise	0	0.05	0.23	1
Resource	0	0.08	0.27	1
Philosophy	0	0.06	0.23	1
InteractiveCues	0	3.00	0.85	5
NameCustomer	0	0.31	0.46	1
Appreciation	0	1.00	0.11	1

Emotion	0	0.77	0.42	1
Attentiveness	0	0.06	0.24	1
<i>InviteBack</i>	0	0.88	0.33	1

Table 5. Content-Tags Descriptions and Summary Statistics (Continued)

4-3. Methodology

$$DV_{i} = \alpha_{i} + \beta_{1}ResponsePos_{i} + \beta_{2}ResponseNeg_{i} + \gamma_{1}ResponseLen_{i}$$
$$+ \gamma_{2}ResponseDelay_{i} + \epsilon_{i} \quad (Equation 1)$$

With the dataset mentioned earlier, we estimate the impact of managerial response on online reputation using pooled OLS regression. DV is a vector variable that includes FutureReviewValence and FutureReviewVolume and i indicates business id to control for business fixed effects. The first equation answers hypotheses 1 and 2, if a managerial response to positive reviews has a positive impact on future review valence and volume.

$$\begin{aligned} DV_i = & \ \alpha_i + \beta_1 Informative \ Cues_i + \beta_2 Interactive Cues_i \\ & + \beta_3 Informative Cues_i Interactive Cues_i + \gamma_1 Response Len_i \\ & + \gamma_2 Response Delay_i + \epsilon_i \ (Equation \ 2) \end{aligned}$$

Next, we measure the effect of informative cues and interactive cues, which are inferred from the text, on future review valence and volume. Each of the variables is connected to the credibility and the benevolence dimension of trust. We regress *FutureReviewValence* and *FutureReviewVolume* on

 $\label{lem:informativeCues} \textit{InformativeCues} \ \ \text{and} \ \textit{InteractiveCues} \ \ \text{and} \ \ \textit{include} \ \ \textit{i} \ \ \text{to control} \ \ \text{for business}$ fixed effects.

5. Results

Table 6 indicates that managerial responses to positive reviews are associated with higher future review valence and not with volume. When positive reviews are responded to, responded reviews are associated with a 0.32-star increase in future review ratings compared to non-responded reviews (Model 2). The results support hypothesis 2, and do not accept hypothesis 1. On the contrary, managerial responses to negative reviews are associated with lower future review valence and volume. The results conflict with prior studies. (Ravichandran and Deng 2022; Wang and Chaudhry 2018)

The biggest difference between this study and prior studies is that we used the restaurant review dataset. Prior studies used the hotel review dataset. We assume that the conflicting results of this study and prior studies can be caused by the fact that the datasets are from different industries. Hotel industries are more commercialized and institutionalized, while restaurants are owned and operated by small and medium-sized companies (even by individuals). This might have caused different managerial behaviors in each market, influencing different reactions from consumers. This needs further investigation by extending analysis to causal inference.

	FutureR	eview	FutureReview	
	Valer	псе	Volur	ne
Model	(1)	(2)	(3)	(4)
ResponsePos	0.50**	0.32**	1.76	0.61
	(0.20)	(0.13)	(1.14)	(0.58)
ResponseNeg	0.15	- 0.19 [*]	1.43	- o.35*
	(0.21)	(0.10)	(0.98)	(0.18)

ResponseLen		0.02**		0.07^*
		(0.01)		(0.04)
ResponseDelay		- 0.003***		- 0.01 ^{**}
		(0.001)		(0.003)
Constant	2.38***	2.01***	1.62***	0.31
	(0.05)	(0.28)	(0.14)	(0.63)
Observations	60,917	7,163	60,917	7,163
R2	0.004	0.03	0.02	0.04
Adjusted R2	0.004	0.02	0.02	0.04
Residual Std.	2.18	2.08	3.43	4.81
Error				
F Statistic	136.00***	46.60***	734.00***	77.10***

Note: Cluster robust standard errors are in parentheses.

*p<0.1; **p<0.05; ***p<0.01

Table 6. The Effects of Managerial Responses to Positive Reviews on Future Review Valence and Volume

Table 7 shows the results for hypotheses 3 to 6. The results suggest that the number of informative cues is associated with a higher review volume and not with valence in this model (Model 2, 6). The number of interactive cues is negatively associated with a review valence and not with review volume. Hypotheses 3, 5, 6 are supported.

For additional analysis, we regressed the dependent variables, FutureReviewValence and FutureReviewVolume, on eight content tags. The results in Model (4) and (8) from Table 7 show that Resource is associated with higher future review volume and valence. This finding supports our initial motivation for the study that businesses can differentiate themselves from competitors by emphasizing their competitive edge and can gain a better reputation. Resource in a response is the main driver for higher future review valence and volume.

Among other content tags, *Attentiveness* is found to be associated with lower *FutureReviewValence*. It means that dealing with specific issues in the corresponding reviews is associated with lower review ratings in the future.

For other control variables, the results are in align with prior studies. Shorter time interval between review and response (*ResponseDelay*) is associated with higher review volume and valence. Longer response (*ResponseLen*) is also associated with higher review volume and valence.

	F	utureRevier	wValence	
Model	(1)	(2)	(3)	(4)
InformativeCues	0.58***	0.23		
	(0.21)	(0.21)		
InteractiveCues	-0.10	-0.30*		
	(0.03)	(0.18)		
InformativeCues	-0.03	0.04		
x InteractiveCues	(0.08)	(0.08)		
InformativeCues				
Expertise			0.19	0.08
			(0.13)	(0.12)
Resource			1.05***	0.86***
			(0.16)	(0.18)
Philosophy			- 0.01	-0.12
			(0.15)	(0.15)
InteractiveCues				
NameCustomer			- 0.31	-0.33*
			(0.19)	(0.18)

Appreciation			0.52	0.19
			(0.31)	(0.30)
Emotion			- 0.20	-0.42
			(0.33)	(0.29)
Attentiveness			0.06	-0.06
			(0.20)	(0.20)
InviteBack			0.16	-0.20
			(0.41)	(0.33)
ResponseLen		0.02***		0.02***
		(0.01)		(0.01)
ResponseDelay		-0.003***		-0.003***
ResponseDelay		-0.003*** (0.001)		-0.003*** (0.001)
ResponseDelay Constant	3.1***		2.38***	
	3.1*** (0.61)	(0.001)	2.38*** (0.49)	(0.001)
		(0.001) 2.97***		(0.001) 2.53***
Constant	(0.61)	(0.001) 2.97*** (047)	(0.49)	(0.001) 2.53*** (0.44)
Constant Observations	(0.61) 5,744	(0.001) 2.97*** (047) 5,744	(0.49) 5,744	(0.001) 2.53*** (0.44) 5,744
Constant Observations R2	(0.61) 5,744 0.02	(0.001) 2.97*** (047) 5,744 0.04	(0.49) 5,744 0.03	(0.001) 2.53*** (0.44) 5,744 0.05
Constant Observations R2 Adjusted R2	(0.61) 5,744 0.02 0.02	(0.001) 2.97*** (047) 5,744 0.04 0.04	(0.49) 5,744 0.03 0.02	(0.001) 2.53*** (0.44) 5,744 0.05 0.05

Note: Cluster robust standard errors are in parentheses.

*p<0.1, **p<0.05, ***p<0.01

Table 7. The Effects of Content Characteristics of Positive Reviews on Future Review Valence and Volume

	Future Review Volume					
Model	(5)	(6)	(7)	(8)		
InformativeCues	4.34***	3.03***				
	(1.20)	(1.07)				
InteractiveCues	-0.73	-1.47				
	(0.82)	(1.10)				
InformativeCues	- 0.42	- 0.14				
x InteractiveCues	(0.48)	(0.47)				
InformativeCues						
Expertise			1.09	0.73		
			(0.79)	(0.74)		
Resource			5.50***	4.82***		
			(1.25)	(1.29)		
Philosophy			1.11	0.66		
			(0.72)	(0.70)		
InteractiveCues						
Name			-1.03	-1.10		
Customer			(0.99)	(0.96)		
Appreciation			0.44	-0.84		
			(1.04)	(0.89)		
Emotion			-2.54	-3·34*		
			(1.79)	(1.86)		
Attentiveness			-0. 78**	-1.27***		
			(0.36)	(0.49)		
InviteBack			1.84	0.49		
			(1.47)	(0.85)		
ResponseLen		0.09*		0.09***		
		(0.06)		(0.04)		
ResponseDelay		-0.01**		-0.01**		
		(0.003)		(0.002)		
Constant	4.99 (3.25)	4.12*	3.11**	3.34***		
		(2.30)	(1.56)	(1.38)		

Observations	5,744	5,744	5,744	5,744
R2	0.12	0.18	0.19	0.23
Adjusted R2	0.12	0.17	0.19	0.23
Residual Std.	4.65	4.5	4.48	4.36
Error				
F Statistic	272.0***	244.0***	167.0***	171.0***

Note: Cluster robust standard errors are in parentheses.

*p<0.1, **p<0.05, ***p<0.01

Table 7. The Effects of Content Characteristics of Positive Reviews on Future Review Valence and Volume (Continued)

6. Conclusion

Here, we summarize findings of the study and discuss academic, practical implications and the limitations of the study. We investigated if managerial responses to positive reviews are effective online reputation management strategy. We first test if managerial responses to positive reviews are associated with higher review volume and valence. Then, we see if and how the content characteristics of positive responses affect future review volume and valence. The regression analysis indicates that when positive reviews are responded, there are 0.32-star increase in review ratings. Its main driver is emphasizing resourcefulness of the restaurant in a response, such as highlighting nice view, location, and friendly staff. Managerial responses to negative reviews are associated with negative review volume and valence in the future. The regression result of the control variables is consistent with prior studies.

We expect that this study will contribute to IS and marketing literatures in three ways. First, the study complements the research on the effect of managerial response on online reputation management. While the number of positive reviews is significantly higher than that of negative reviews, prior studies focused on the effect of managerial responses to negative reviews. By analyzing the effect of managerial responses to positive reviews, our study moves research of online reputation management one step forward to completion. Second, we used machine learning techniques to extract information from unstructured data. We defined the content tags according to prior literature and industry guidelines, and let the classifiers automatically detect the tags of managerial responses to positive reviews. We

believe that future research can extend our classification. Lastly, our study provides a practical implication for businesses on how to respond effectively to increase the chance of customer acquisition. Businesses can emphasize its resourcefulness to differentiate themselves from competitors and gain better online reputation. We think that the content analysis in this study will provide meaningful insight on sellers' response strategy.

The study is not without limitations. First, our analysis is at association level. There are a lot of covariates that should be controlled for to resolve endogeneity, such as restaurant quality, size, capability, proportion of responses to positive reviews and negative reviews (business-level covariates), response length, similarity between responses (response-level covariates), and seasonality (time-level covariates). We plan to include time-varying variables and fixed effects in analysis in the future. Second, the dataset consists of restaurant review data from New York. This may limit the generalizability of the study since restaurant behaviors would be different from those in New York and in Hawaii. We plan on collecting data from different cities such as Hawaii and Boston.

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Abstract

긍정적인 리뷰에 대한 관리자의 답변은 실제로 다수 관찰되지만 긍정적인 리뷰에 대해 관리자가 어떻게 반응해야 효과적으로 온라인 평판 관리를 할 수 있는지에 대한 연구는 거의 없다. 이 연구는 긍정적인 리뷰에 대한 관리자 답변의 효과를 연구하는 것을 목표로 한다. 구체적으로, 이 연구는 긍정적인 리뷰에 대한 관리자의 답변이 향후리뷰 개수와 리뷰 평점과 상관관계가 있는지 조사한다. 또한, 관리자답변의 내용적인 특성이 향후 리뷰 개수와 평점과 상관관계가 있는지 연구한다. Trip Advisor에서 2018년 1월 1일부터 2022년 9월 19일까지 뉴욕에 위치한 2,214개 레스토랑의 60,916건의 리뷰를 크롤링하여 데이터를 수집, 분석을 진행하였다 분석 결과에 따르면, 긍정적인 리뷰에 관리자가 응답할 때, 응답하지 않을 때보다 미래 리뷰 평점이 0.32 점 증가한다. 이러한 평점 증가는 관리자가 긍정적인 댓글답변을 달 때, 비즈니스의 자원을 강조할 때 더욱 두드러지는 현상으로보인다.