



The role of review responses in shaping online review content and review space dynamics

HanByeol Stella Choi¹ · Junyeong Lee² · Chanhee Kwak³ · Jinyoung Min⁴

Received: 26 May 2025 / Accepted: 29 September 2025
© The Author(s) 2025

Abstract

Communication on online review platforms has Please check if the affiliations are captured and presented correctly and amend if necessary. Traditionally involved reviewers detached from the entities under review. However, many platforms have now introduced the capability for targets (e.g., business owners) to respond directly to reviews, thereby transforming the nature of interactions within review spaces. This change indicates that reviewers may now engage with both a general audience and the review targets themselves. To address this shift, this study explores how targets' responses influence subsequent reviews by investigating changes in review characteristics such as length, cognitive content, and affective expression. Yelp and TripAdvisor have permitted businesses to respond to reviews since 2009; thus, data from these platforms were used to employ a difference-in-differences model to analyze the impact of response intensity, response diversity, and review-response similarity on subsequent review attributes. Our findings indicate that greater response intensity and diversity are positively associated with the length of the text and the cognitive language used in subsequent reviews. Moreover, higher review-response similarity enhances the affective tone of subsequent reviews. These results highlight the complex impact of review responses from the reviewed targets on review space by changing platforms' information quality and relationship dynamics.

Keywords Online review · Review space dynamics · Review response · Response intensity · Response diversity · Review-response similarity

JEL Classification M15

Responsible Editor: Marianna Sigala

✉ Jinyoung Min
jymin@cau.ac.kr
HanByeol Stella Choi
hbschoi@mju.ac.kr
Junyeong Lee
junyeong.lee@cbnu.ac.kr
Chanhee Kwak
chk@kangnam.ac.kr

¹ Department of Management Information Systems, Myongji University, Korea, 34, Geobukgol-Ro, Seodaemun-Gu, 03674 Seoul, Republic of Korea

² Department of Management Information Systems, Chungbuk National University, 1 Chungdae-Ro, Seowon-Gu, 28644 Cheongju, Chungbuk, Republic of Korea

³ Department of Artificial Intelligence Convergence, Kangnam University, 40, Gangnam-Ro, Giheung-Gu, Yongin-Si, 16979 Gyeonggi-do, Republic of Korea

⁴ Department of Industrial Security, College of Business & Economics, Chung-Ang University, 84 Heukseok-Ro, Dongjak-Gu, 06974 Seoul, Republic of Korea

Introduction

In the context of computer-mediated communication, two parties—the sender and receiver—communicate through a specific channel (Walther, 1996). When this channel is a product or service review platform, the online review becomes a form of communication between reviewers (Moore & Lafreniere, 2020). Specifically, message senders are those who write reviews to express their opinions, and receivers read the reviews to gather information. In the review context, senders and receivers were initially similar, as they were distanced from the review target. That is, communication on review platforms was limited to past, current, and potential consumers and did not involve the review target. However, this has changed as some platforms now allow a review target (e.g., the owner or manager of a reviewed business) to respond to reviews. Prior to this, reviewers may have been uncertain about whether their voices were heard; however, the targets' ability to respond now signals that reviewers' messages are being monitored (Chevalier et al., 2018). This shift indicates that reviews can be written not only to provide useful information to other consumers but also to business owners. Although businesses' actions are similar to those of reviewers in receiving and sending messages, they differ in that they focus on their own business in response to reviews. As these responses can signal businesses' attitudes and expectations (Chen et al., 2019; Deng & Ravichandran, 2024), their existence may influence how reviewers write messages (Hung et al., 2024) and thus affect the overall dynamic of review spaces.

Most prior studies on review responses have understood them as a business strategy for improving customer-related business performance by decreasing the adverse impact of negative reviews and magnifying positive ones (Deng & Ravichandran, 2024; Ku et al., 2024; Li et al., 2018; Rathjens et al., 2023; Wang & Chaudhry, 2018; Wu et al., *in press*). Particularly, these studies focus on ratings (Hung et al., 2024; Proserpio & Zervas, 2017; Ren et al., 2024; Sheng et al., 2021; Wu et al., *in press*), customer emotions (Hung et al., 2024), consumption likelihood (Wang et al., 2020), and revenue growth (Wu et al., *in press*). However, this perspective of considering responses as strategies may limit the understanding of the review space in the era of artificial intelligence (AI). As AI technology becomes increasingly prevalent, it allows for the creation and customization of responses at a significantly lower cost (Tan et al., 2025; Zhang et al., 2025). This makes it easier to achieve customer-related performance goals with relatively little effort. Consequently, the immediate outcomes of these responses may provide clearer insights into how the review landscape will evolve in the near future, rather than focusing solely on strategic efforts and subsequent performance

metrics. It is important to recognize that understanding the changes in review dynamics, prompted by the ability of review targets to respond, requires a perspective that goes beyond businesses' strategic initiatives for managing reviews.

In addition, prior to review targets' participation, reviews were primarily created and consumed by a relatively homogeneous group whose main intention was to decide whether to use certain products or services. In contrast, targets differ from consumers in their intentions, as their ultimate goal is to shape consumers' perceptions and influence their behaviors (Lopes et al., 2023; Wang et al., 2020). Targets' participation affects subsequent reviews by changing the atmosphere and overall informational value of the review space, potentially influencing how these spaces evolve. Numerous studies on online communication have examined how prior users' messages affect subsequent communication (Choi et al., 2022; Flanagin, 2017). However, most research has overlooked the role of participant heterogeneity in shaping subsequent reviews. Thus, investigating review space dynamics from the perspective of user heterogeneity can provide deeper insights into how communication evolves when past interactions influence future ones.

Therefore, this study aims to explore how the responses of a target influence the nature of subsequent reviews. It seeks to explain the impact of these responses by examining how they alter the dynamics of the review space, specifically in terms of review length as well as the cognitive and emotional characteristics of later reviews. Review length is important as it can indicate the helpfulness of a review (Lutz et al., 2022; Mudambi & Schuff, 2010), thereby influencing the audience's evaluation (Mudambi & Schuff, 2010). Cognitive characteristics refer to a review's informativeness (Wang et al., 2023), signaling its information quality (Mackiewicz & Yeats, 2014). Perceptions of a review may affect readers' evaluations of products and services (Jiang et al., 2021); thus, the perceived helpfulness and informativeness of reviews can impact consumers' overall evaluation of the review space and the quality of the information it provides. Affective characteristics often refer to the relational value of a review (Huang et al., 2017). A review space ultimately acts as a communication channel between users; thus, its relational value can affect how those within the space communicate through reviews (Derks et al., 2008). Therefore, review length as well as cognitive and affective language can help explain review space characteristics.

To answer our research question, we implemented a difference-in-differences model using field data from two leading restaurant review sites, Yelp and TripAdvisor, which have both allowed business owners to respond to reviews since 2009. In our research design, the treatment group consists of 43,747 reviews from 56 restaurants that began allowing review responses during the observation period,

whereas the control group includes 27,952 reviews from 37 restaurants that did not implement this feature. To understand how responses affect subsequent review characteristics, we first capture these characteristics in three aspects: the frequency of responses (response intensity), the diversity of responses in terms of length (response diversity), and the textual similarity between responses and reviews (review-response similarity). Then, we test how they affect the length as well as the cognitive and affective characteristics of subsequent reviews.

The following section provides a detailed review of the existing literature related to our research and its theoretical background. Following this, we suggest our hypotheses and test them using empirical analysis. We then discuss the results in detail. The practical and theoretical implications of the findings are presented alongside the limitations and suggestions for future studies.

Literature review

Review responses as a strategy to enhance business performance

Reviews have become a dominant information source on platforms. Consumers' value reviews as they offer evaluations of products and services (Lee et al., 2021; Ruiz-Mafe et al., 2018). For instance, consumers may choose to access reviews to support their decision-making before purchasing products, visiting restaurants, reserving hotels, or ordering food (Sun et al., 2019). Previously, businesses had little control over the situation; however, they can now engage on such platforms by responding to reviews. These responses are of managerial importance as they can enhance customer engagement and enable the delivery of customized services and experiences (Lopes et al., 2023; Wang et al., 2020). Consequently, many researchers have studied the effectiveness of review responses. Most literature in this domain views review responses as strategic customer management initiatives; thus, the predominant areas of interest within these studies can be summarized as follows: (1) which aspects of a business can be improved based on the responses, and (2) what kinds of response strategies can be implemented and how those strategies can be articulated depending on the situation.

For the benefit of businesses, related research has studied the effect of responses on increasing review volume (e.g., Lopes et al., 2023; Proserpio & Zervas, 2017; Xie et al., 2014), as a sufficient volume is necessary for leveraging reviews for strategic business use. Studies have also examined how to use responses to increase review usefulness (Zhou et al., 2023) and decrease the harm of negative

reviews (Li et al., 2018; Wang & Chaudhry, 2018). These actions can help improve customer-related performance indices, such as ratings (Proserpio & Zervas, 2017; Ren et al., 2024; Sheng et al., 2021; Wu et al., *in press*), customer emotions (Hung et al., 2024), consumption likelihood (Wang et al., 2020), and revenue growth (Wu et al., *in press*). Specifically, Li et al. (2018) found that responses can indeed mitigate the adverse impact of negative reviews by reducing the attribution of these reviews to the target firms. Furthermore, Wu et al. (2024) distinguished between the impacts of responses to positive and negative reviews, finding that the ratio of review responses to positive reviews leads to an increase in subsequent customer review ratings and revenue. However, the ratio of review responses to negative reviews can decrease customer review ratings and revenue in the short run, but still contribute to improvements in the long run, suggesting that, although the effect timing varies depending on the review type, responses can help improve product and business-related performance.

As the impact of the responses becomes clear, researchers have begun to examine various response strategies. Some have emphasized the review-response pair strategy, which compares responses to the corresponding reviews, such as addressing a reviewer in a response (Chen et al., 2019; Kumar et al., 2018; Zhang et al., 2024), tailoring response topics similar to the corresponding review (Deng & Ravichandran, 2024; Wu et al., *in press*; Zhou et al., 2023), and using a similar language style in responses (Darani et al., 2023; Ren et al., 2024). Others have focused on a response variation strategy, which compares responses, including different responses to each review (Li et al., 2018; Liu et al., 2021; Lopez-Lopez et al., 2025), response promptness and intensity (Sheng et al., 2021), and leaving rational or emotional cues in responses (Ravichandran & Deng, 2023; Zhang et al., 2023).

Specifically, Zhou et al. (2023) revealed that topic consistency between the review response and the corresponding review can enhance helpfulness. Similarly, Ren et al. (2024) examined the effect of language style matching between reviews and responses and found that the match leads to a subsequent consumer rating increase. Furthermore, Ravichandran and Deng (2023) found that responding to customer complaints with rational cues rather than emotional ones can positively affect future review valence. Hung et al. (2024) also found that the emotions presented in previous reviews can impact subsequent reviews; thus, responses can be used to regulate these emotions, such as by expressing gratitude to reinforce positive emotions and apologizing, explaining, and empathizing to address negative emotions. Further delving into these strategies demonstrates the importance of articulating and tailoring a response depending on the situation. For instance, Li et al. (2018) suggested that when dealing with product failure reviews, accommodative

responses are more effective than defensive ones; however, when confronting general negative reviews, an opposing strategy is more ideal. Through experimentation, Wang et al. (2020) revealed that using highly tailored responses to negative reviews can be a good strategy for fostering consumption intentions, as the response's applicability to reviews can likely address complaints. However, for positive reviews, a less tailored response may be more effective, as highly tailored ones may be perceived as simply reiterating the original message. They also examined three strategies for selecting which reviews to respond to in order to encourage continued consumption: responding to all, responding at random, or only responding to extreme reviews. They suggested that random responses are more effective for positive reviews; however, all negative and extreme reviews should receive a response. Rathjens et al. (2023) examined the moderating effect of restaurant ratings on the impact of responses to negative reviews and found that restaurants with relatively higher ratings were more effective at increasing customer satisfaction by providing tailored review responses to negative reviews. Additionally, Zhou et al. (2023) revealed that topic consistency between reviews and responses enhances review helpfulness when the positive emotional intensity in the review is high. Deng and Ravichandran (2024) categorized reviews based on review sentiment and evaluation criteria and determined which response strategies—tailored or standardized—are more effective. They found that a tailored response is more appropriate for reviews with both positive and negative sentiments that evaluate service or product characteristics or reviews with only positive sentiments evaluated by a reviewer's subjective criteria. Conversely, standardized responses are ideal only for positive reviews that evaluate product characteristics or reviews that are both positive and negative, based on subjective criteria. Jin et al. (2023) investigated the role of personalized review responses and demonstrated that these responses enhance review helpfulness. Their findings were moderated by review inconsistency (negative ratings with positive textual sentiment) and mediated by perceived response helpfulness. That is, personalized review responses to inconsistent negative reviews significantly shape consumers' helpfulness assessments of reviews through perceptions of review helpfulness. Furthermore, Ku et al. (2024) showed that appropriate response strategies vary by situation. For example, active-constructive responses are suitable for increasing the impact of positive reviews, whereas passive-constructive responses can mitigate the damage from negative reviews.

Although the previous literature has provided valuable knowledge on online reviews and responses, considering responses solely as a business strategy may be an overly simplistic approach to understanding the entirety of the review space. From this perspective, the goal of responses is perceived as increasing customer-related performance metrics

such as ratings and purchase intentions. Although examining the effects of strategically tailored response efforts on customer-related performance metrics provides valuable insights for businesses, understanding these responses as strategic endeavors may fail to address the reality of review spaces, as it becomes increasingly easy to manipulate responses and the resulting customer-related performance metrics. Recent research has shown that AI can easily generate review responses resembling those written by humans, and people tend to react in the same way they do to human responses unless they are aware they are AI-generated (Tan et al., 2025; Zhang et al., 2025). As AI adoption expands across industries, the importance of response-tailoring strategies may diminish as reviewers take response efforts for granted. Therefore, moving away from using responses as a strategy to improve business performance, it is necessary to examine the more immediate consequences of responses to extend and enrich our knowledge on the topic. We believe understanding responses as a fundamental form of communication and how they change online review space dynamics can help achieve this goal.

Review responses from the perspective of online review space dynamics

Existing studies on online communication have focused on the importance of changes in the communication space, shown by shifts in users' communication styles. These studies tend to focus on how the social features in communication spaces (Lopes et al., 2023; Tep et al., 2022) or the characteristics of original posts on social media (Qian et al., 2023) affect dynamics. However, few have investigated the impact of interactions between reviewers and business owners on subsequent reviewers' behavior from the perspective of online communication and space dynamics in the online review context. Therefore, understanding the changes in review space dynamics is important from the perspectives of both online communication and business performance. If reviews change due to responses, the entire review space and the resulting information can also be altered. Numerous studies in various fields have already shown how responses can change reviewers' contribution efforts (Sheng, 2019) and perceptions toward review systems (Xu et al., 2020), suggesting that a target's responses can influence review space dynamics.

We propose that social presence may be behind this dynamic change. Social presence refers to "the degree of salience of the other person in the interaction and the consequent salience of the interpersonal relationships" (p.65, Short et al., 1976). In a computer-mediated communication environment, social presence is defined by the individuals' awareness of their connections with others or their interactivity (Huang et al., 2017). In online spaces, users' sense

of social ambience (referred to here as social presence) is shaped by cues such as text, voice, or visual aids (Hess et al., 2009; Sia et al., 2002).

When social presence reaches a certain level, it can influence how users behave in a space. For example, higher social presence can enhance positive attitudes (Cyr et al., 2007), foster agreeableness (Hess et al., 2009), and affect how individuals express their preferences, opinions, and even hostility (Pu et al., 2020). A stronger presence tends to encourage individuals to present themselves more positively (Molinillo et al., 2018) and alters linguistic patterns, such as the use of cognitive or affective words, through changes in mental processing (Huang et al., 2017).

Given its behavioral impact, building social presence through appropriate tools and strategies has become a key interest for those managing online spaces (Kou et al., 2025). In the online review space, social presence is primarily constructed through user-generated reviews. When the target (e.g., a business owner) being reviewed gains the ability to respond to reviews, the combination of reviews and responses jointly shapes the perceived social presence. Although the target cannot directly control reviews, their responses are under their control. Thus, they may strategically decide how to respond. As a result, social presence can be established through response frequency, reply promptness, and message content (Sheng et al., 2021). Active and thoughtful responses can signal that the reviewer's comments are being monitored and valued, thereby increasing feelings of social presence (Shen et al., 2015) and eventually changing the dynamics of the review space.

In this study, we take the perspective that the target's response management is a form of social presence, examining how such cumulative efforts influence the overall dynamics of online review spaces.

Linguistic changes due to shifts in review space dynamics

Review characteristics are inherently represented by linguistic features, as the dynamics of a review space are determined by how people send and receive review messages, and the reviews are primarily written in text. In particular, the function of reviews extends beyond merely transmitting facts about a product. Rather, they also allow consumers to express their subjective experiences, emotions, and sentiments (Fan et al., 2022; Park et al., 2023). Such characteristics highlight that online reviews embody not only informational value but also relational value. The coexistence of these two dimensions implies that both value types can exert a salient and consequential influence on potential consumers' decision-making processes and review authors' motivations. For example, the cognitive and affective processes

guiding a writer's choices can be discerned through linguistic features like word selection (Wang et al., 2023). The emotions represented in word choices can impact the affective or cognitive mode of those who read the text and further influence their writing behaviors (Greifeneder et al., 2011). This suggests that the linguistic features of a review affect the tone and demeanor of the associated platform, thereby shaping its overall atmosphere (Hou & Ma, 2022). Examining the linguistic patterns in subsequent reviews offers insights into how responses shape the broader discourse within the review space, providing a more stable and less easily manipulated indicator of the underlying dynamics (Lopes et al., 2023). Moreover, as AI-generated responses aim to increase customer satisfaction, they can help enhance a firm's financial performance; thus, it is important to examine how strategically tailored responses reshape the dynamics of the entire review space by influencing the language used in subsequent reviews, rather than solely focusing on customers' immediate reactions.

Particularly, this study focuses on changes in review space dynamics by examining the linguistic features of subsequent reviews, represented by text length (Pu et al., 2020), which can indicate the helpfulness of reviews (Lutz et al., 2022; Mudambi & Schuff, 2010; Zhou et al., 2023) and word choice, referring to text sentiment (Huang et al., 2017). Specifically, word choice encompasses the cognitive characteristics that determine a review's informativeness (Wang et al., 2023) and the affective characteristics that imply its relational value (Huang et al., 2017). Therefore, we investigate how response delivery induces subsequent review generation by examining text length (Sun et al., 2019) and the cognitive or affective characteristics in texts (Li & Huang, 2020) to explore how review space dynamics change.

Hypotheses development

To explore how review responses affect the dynamics of review spaces, we analyze the characteristics of subsequent reviews in terms of text length and the cognitive and affective language used by investigating how responses and their content are managed and tailored. Based on a synthesis of the existing literature, we examine response intensity, response diversity, and review-response similarity.

Studies on response intensity suggest it acts as a signal from respondents that they are indeed engaged in the review space (Sheng et al., 2021). Literature on response strategy also emphasizes its importance, specifically in responding to reviews in a tailored manner (Li et al., 2018; Wang et al., 2020). Responsiveness can be measured based on response diversity, referring to varied writing styles instead of standardized responses (Sheng et al., 2021), and review-response similarity, which is the textual similarity between the review

and the associated response (Deng & Ravichandran, 2024; Wang & Chaudhry, 2018; Zhou et al., 2018).

The impact of response intensity

This study defines review response intensity as the frequency with which a business responds to reviews on a review page. This intensity indicates responders' concerns over reviewers' reactions to products or services (Song & Tian, 2020). As the communication between reviewers and responders is public and thus visible to all participants in the review space (Wei et al., 2013), the response intensity signals that future reviews will likely be read (Cheung et al., 2014). It also indicates responders' willingness to address reviewers' feedback and improve their products or services (Zhang et al., 2019). Therefore, the positive signal from high response intensity favorably affects reviewers' perceptions of products or services (Sheng et al., 2021) and their trust in them (Sparks et al., 2016), thus enhancing their online engagement (Kwok & Xie, 2016; Li et al., 2017; Xie et al., 2014). Greater engagement means that reviewers spend more time and effort in review spaces, which can also be reflected in longer reviews (Grewal & Stephen, 2019; Pan & Zhang, 2011). Thus, we argue that response intensity can increase review length and propose the following hypothesis:

H1: The more review responses on a review page, the longer the length of subsequent reviews will be.

The impact of response diversity

Regarding review response diversity, if responses are tailored to vary their content, readers assume the responders prioritize communication with reviewers (Xu & Zhao, 2022). In contrast, if responses are uniform, often represented by automatically generated response content, reviewers may feel that the responders are unconcerned (Sheng et al., 2021) and lack effort, attention, and sincerity (Wu et al., 2024). Thus, reviewers may consider these responses less credible and even perceive them as general advertisements (Mauri & Minazzi, 2013). Uniform or monotonous responses that do not offer additional information are perceived as less effective (Palese et al., 2021). In contrast, diverse responses, along with reviews, provide readers with more useful information about products or services. As reviews can include reviewers' heterogeneous preferences (Li & Hitt, 2008), the responses can provide further information in meeting these diverse preferences, implicitly offering readers guidance on how to process the information to address their needs (Garaus et al., 2015; Gillespie et al., 2018; Kopp et al., 2018). Comprehending diverse responses inevitably requires readers' cognitive processing (Jackson & Farzaneh, 2012; Sun et al., 2019). Due to social norms,

people feel pressured to engage in behaviors similar to those in their social surroundings, even in online review spaces (Choi et al., 2022). Thus, readers who use cognitive processing to comprehend information will also apply this same process when writing reviews. In other words, when reviewers find review spaces informative due to diverse responses, they may feel they should also leave informative reviews by using more cognitive language to provide information and constructive feedback.

Additionally, a more informative review space is often characterized by longer reviews. The text length of online reviews can serve as an indicator of quality (Chua & Banerjee, 2015) and reflects the reviewer's level of involvement (Pan & Zhang, 2011). Prior studies have consistently shown that longer reviews contain more detailed descriptions and specifics about consumers' experiences, providing readers with more useful information to make informed decisions (Chevalier & Mayzlin, 2006; Srivastava & Kalro, 2019). Therefore, we suggest that review response diversity positively affects review informativeness, particularly by increasing the cognitive language used in subsequent reviews and their length. Thus, we propose the following hypothesis.

H2: The more diverse the responses become, (a) the more cognitive language and (b) the longer the length will be in subsequent reviews.

The impact of review-response similarity

Regarding review-response similarity, if a responder uses language similar to that of a reviewer, the reviewer may perceive an enhanced intimacy with the responder (Sheng et al., 2021). Active listening theory emphasizes the importance of engaging with what reviewers express by using techniques such as repeating, paraphrasing, and adapting language. These actions are essential for building connections and improving communication effectiveness (McMains & Lanceley, 2003; Vecchi et al., 2005; Wu et al., *in press*). Similarly, empathy theory suggests that responses that significantly align with review content demonstrate personalized attention, helping to alleviate reviewers' adverse feelings by showing that the responders understand their emotions (Dickinger & Bauernfeind, 2009). Thus, such empathetic responses are expected to influence subsequent reviewers' positive evaluations and emotions (Ren et al., 2024; Zhang et al., 2020). The empathy, intimacy, and emotion established in the review space through review-response textual similarity can increase the use of affective language in subsequent reviews. Therefore, we hypothesize the following:

H3: The more similar the textual form of a response is to a review, the more affective language will appear in subsequent reviews.

Fig. 1 Yelp review page without review responses

Empirical strategy

Data

We obtained our data from two leading restaurant review sites in the USA: Yelp and TripAdvisor. These sites adopted review response features in April and March 2009, respectively, and in our dataset, TripAdvisor's review response has appeared since July 2014. Yelp and TripAdvisor are appropriate for analyzing the impact of review responses on

different platforms, as both have review response features and provide similar restaurant lists.

We collected review data for a matched set of restaurants in five major cities in the USA: New York, Los Angeles, Chicago, Philadelphia, and Phoenix. The data contains 93 restaurants appearing on both websites from April 2004 to July 2021, covering the periods before and after the platforms allowed review responses. Our dataset comprises review content, review responses, reviewer information (such as the reviewer's screen name and locality),

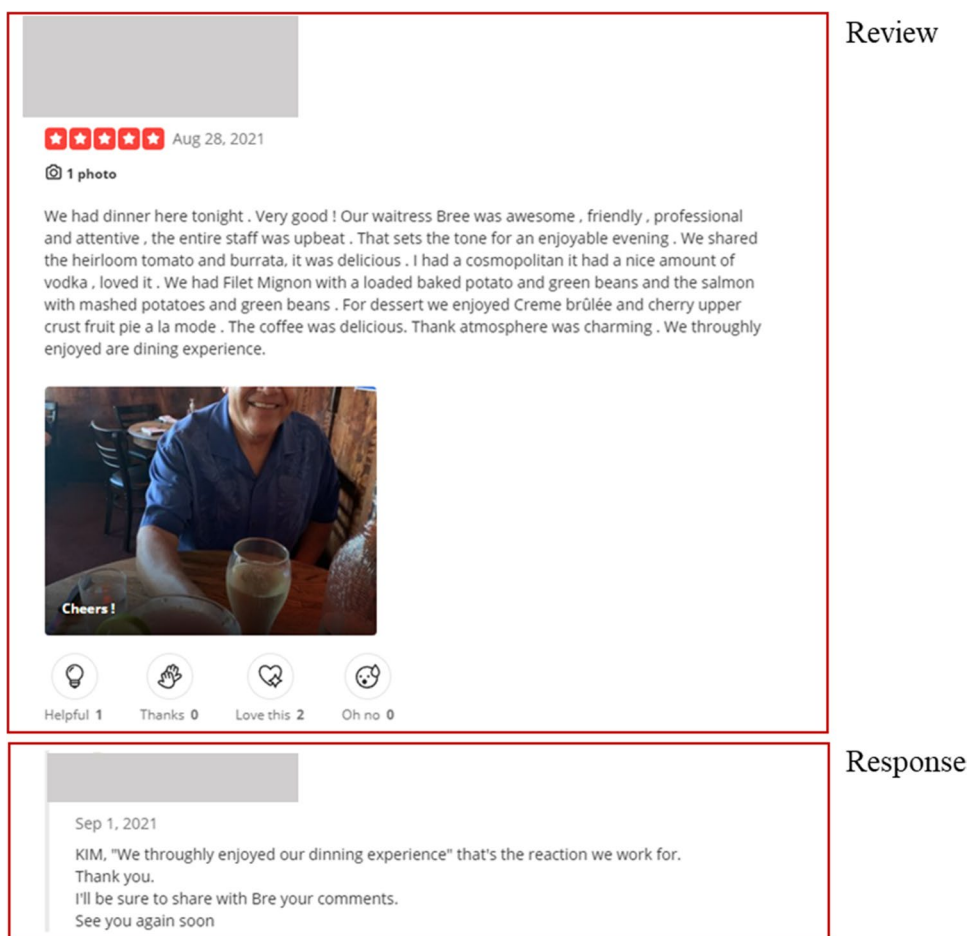
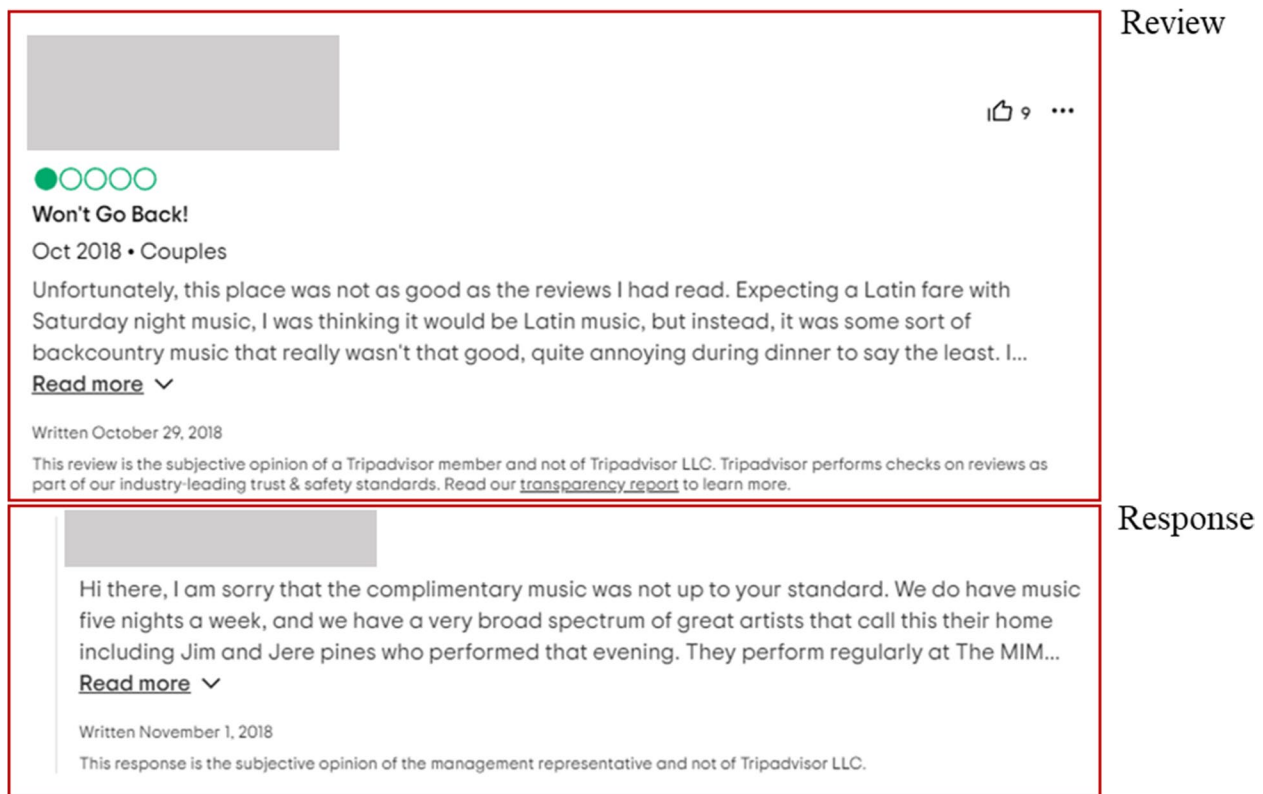
Fig. 2 Yelp review page with review responses

Fig. 3 TripAdvisor review page without review responses**Fig. 4** TripAdvisor review page with review responses**Table 1** Descriptive statistics of the target data

		Before review responses	After review responses
Reviews	Total number of reviews	39,460	32,239
	Average number of reviews per restaurant	424.301	346.656
Responses	Total number of responses	4,667	
	Average number of responses per restaurant	50.183	

Table 2 Summary of the variable measurements

Variable type	Variable	Measurement
Independent variables	ResponseIntensity _{ijt}	The number of existing review responses within a focal restaurant review page at time t , at which review j of restaurant i was written
	ResponseDiversity _{ijt}	Variance of the length of existing responses at time t , at which review j of restaurant i was written
	ReviewResponseSimilarity _{ijt}	The sentence similarity between review responses and the corresponding review at time t , at which review j of restaurant i was written (generated by calculating the average similarity score of existing review-response pairs using cosine similarity with a Word2Vec model)
Dependent variables	ReviewLen _{ijt}	The number of words contained in review j of restaurant i at time t
	CognitiveLang _{ijt}	The number of words that are associated with cognitive functions like thinking, knowing, and understanding (e.g., “because,” “not,” or “make”) divided by the total number of words contained in review j of restaurant i at time t
	AffectiveLang _{ijt}	The number of words that are related to emotions (e.g., “happy,” “sad,” or “fun”) divided by the total number of words contained in review j of restaurant i at time t
Control variables	NumPriorReview _{ijt}	The number of existing reviews at time t , at which review j of restaurant i was written
	PriceLine _i	Price level of restaurant i , categorized into five levels
	Menu _i	Restaurant cuisine type of restaurant i , categorized based on the description written on the restaurant review page (170 categories)
	SameState _{ijt}	Whether the reviewer of review j of restaurant i at time t lives in the same city as the restaurant (1: in-state, 0: out-of-state)

and restaurant information (such as restaurant type, price range, and address). Figures 1, 2, 3, and 4 present screenshots of review pages for each website, and Table 1 displays the descriptive statistics of the target data.

Measurements

Dependent variables

We employed Linguistic Inquiry and Word Count (LIWC), a text analytics tool, to measure the linguistic features of reviews. LIWC calculates the scores of various sentiment categories within text documents based on the ratio of the number of words matched to previously defined keyword dictionaries (Pennebaker et al., 2015). This tool has previously been used in online review literature (Ren et al., 2024), making it relevant to our study. We leveraged LIWC’s word count measures for review j of restaurant i at time t (ReviewLen_{ijt}), the sentiment score for the cognitive language of review j of restaurant i at time t (CognitiveLang_{ijt}), and the sentiment score for the affective language (AffectiveLang_{ijt}) of review j of restaurant i at time t . Owing to high skewness, we employed a natural log for each measurement as a variable; thus, we used $\ln(\text{ReviewLen}_{ijt})$, $\ln(\text{CognitiveLang}_{ijt})$, and $\ln(\text{AffectiveLang}_{ijt})$.

Independent variables

For responses, we measured ResponseIntensity_{ijt} (Sheng et al., 2021), ResponseDiversity_{ijt} (Li et al., 2018; Liu

et al., 2021; Lopez-Lopez et al., 2025; Wu et al., *in press*), and ReviewResponseSimilarity_{ijt} (Darani et al., 2023; Deng & Ravichandran, 2024; Ren et al., 2024; Zhou et al., 2023), as shown in Table 2. Because of the high skewness of the variables, we employed the natural log for each independent variable; thus, we used $\ln(\text{ResponseIntensity}_{ijt})$, $\ln(\text{ResponseDiversity}_{ijt})$, and $\ln(\text{ReviewResponseSimilarity}_{ijt})$.

Control variables

We controlled the factors related to review generation and considered the characteristics of the restaurant and the reviewer. As summarized in Table 2, we measured NumPriorReviews_{ijt} (the natural log is used for this measure and is represented as $\ln(\text{NumPriorReviews}_{ijt})$), restaurant i ’s menu type (Menu_i), the price range of restaurant i (PriceLine_i), and reviewer characteristics (SameState_{ijt}).

Analysis

We employed a difference-in-differences (DID) model to estimate the causal influence of review responses (Bertrand et al., 2004). The model uses continuous variables such as response intensity, response diversity, and review-response similarity as treatment variables. Notably, the restaurant on each website adopted review response features at different times. Therefore, we employed a two-way fixed effect DID model with continuous treatment and staggered timing (Callaway et al., 2024). It provides a methodology for analyzing

Table 3 Descriptive statistics of the measurements (observations = 71,699)

		Mean	Std. Dev	Range (min–max)
Independent variable	ResponseIntensity _{ijt}	32.147	97.673	0–700
	ResponseDiversity _{ijt}	137.097	242.233	0–1732.636
	ReviewResponseSimilarity _{ijt}	0.059	0.067	0–0.380
Dependent variable	ReviewLen _{ijt}	104.577	95.887	0–1670
	CognitiveLang _{ijt}	9.318	4.438	0–40
	AffectiveLang _{ijt}	8.667	4.759	0–50
Control variable	NumPriorReview _{ijt}	582.167	545.264	0–2688
	PriceLine _i	1.993	0.892	0–4
	Menu _i	61.498	49.622	0–169
	SameState _{ijt}	0.617	0.486	0–1

Table 4 Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)ln(ResponseIntensity _{ijt})	1.000									
(2)ln(ResponseDiversity _{ijt})	0.735*	1.000								
(3) $\ln\left(\frac{\text{Review}}{\text{ResponseSimilarity}_{ijt}}\right)$	0.732*	0.893*	1.000							
(4)ln(ReviewLen _{ijt})	−0.032*	−0.066*	−0.053*	1.000						
(5)ln(CognitiveLang _{ijt})	0.000	−0.018*	−0.019*	0.284*	1.000					
(6)ln(AffectiveLang _{ijt})	0.050*	0.043*	0.054*	−0.393*	−0.159*	1.000				
(7)ln(NumPriorReview _{ijt})	0.295*	0.254*	0.227*	−0.077*	0.027*	−0.005	1.000			
(8)PriceLine _{ijt}	0.089*	0.135*	0.158*	−0.034*	−0.034*	0.027*	0.024*	1.000		
(9)Menu _i	−0.249*	−0.064*	−0.141*	−0.089*	−0.072*	−0.007	−0.236*	0.337*	1.000	
(10)SameState _{ijt}	0.061	0.012*	0.015*	0.056*	0.046*	−0.003	−0.036*	−0.127*	−0.209*	1.000

continuous treatment effects where the treatment timing differs across treated units. The following equation describes the estimation model. First, LinguisticFeatures_{ijt} represents the dependent variables: *ReviewLength_{ijt}*, *CognitiveLang_{ijt}*, and *AffectiveLang_{ijt}*. Second, ResponseFactors_{ijt} represents the independent variables: *ResponseIntensity_{ijt}*, *ResponseDiversity_{ijt}*, and *ReviewResponseSimilarity_{ijt}*. *AfterResponse_{ijt}* represents whether a review was responded to at the time when it was written, and *Controls_{ijt}* represents the control variables. *R_i* is a restaurant fixed effect, *T_t* is a time fixed effect, and *S_j* is a site fixed effect. Table 3 shows the descriptive statistics of the measurements.

Table 4 presents the correlation matrix, which shows the relationship between variables. If the correlation between these variables exceeds 0.9, the model is subject to multicollinearity (Chan et al., 2022). None of the pairs of independent and control variables in our model exceeds 0.9; therefore, our model is not subject to multicollinearity.

The following equation describes the estimation model. ResponseFactors_{ijt} represents the independent variables, *AfterResponse_{ijt}* represents whether a review is responded

to at the time it was written, and *Controls_{ijt}* represent the control variables. *R_i* is a restaurant fixed effect, *T_t* is a time fixed effect, and *S_j* is a site fixed effect.

$$\begin{aligned} \text{LinguisticFeatures}_{ijt} = & \beta_0 + \beta_1 \text{ResponseFactors}_{ijt} \\ & \times \text{AfterResponse}_{ijt} \\ & + \beta_2 \text{AfterResponse}_{ijt} \\ & + \text{Controls}_{ijt} + R_i + T_t + S_j \\ & + \epsilon_{ijt} \end{aligned}$$

Results

Table 5 summarizes the impact of review response strategies on the linguistic characteristics of subsequent reviews. Row1 of Table 5 shows the positive impact of response intensity on subsequent review length, supporting H1. Regarding the coefficient, a 1% increase in the number of review responses results in a 0.94% increase

Table 5 The impact of review-response similarity

	$\ln(\text{ReviewLen}_{ijt})$	$\ln(\text{CognitiveLang}_{ijt})$	$\ln(\text{AffectiveLang}_{ijt})$
$\ln(\text{ResponseIntensity}_{ijt}) \times \text{AfterResponse}_{ijt}$	0.009* (0.004)	0.004 (0.003)	− 0.002 (0.003)
$\ln(\text{ResponseDiversity}_{ijt}) \times \text{AfterResponse}_{ijt}$	0.018*** (0.005)	0.008* (0.004)	− 0.007* (0.003)
$\ln(\text{ReviewResponseSimilarity}_{ijt}) \times \text{AfterResponse}_{ijt}$	− 0.736** (0.243)	− 0.289 (0.188)	0.396** (0.149)
$\text{AfterResponse}_{ijt}$	− 0.019 (0.034)	− 0.016 (0.026)	− 0.001 (0.021)
$\ln(\text{NumPriorReview}_{ijt})$	− 0.051*** (0.005)	0.002 (0.003)	0.006* (0.003)
PriceLine_i	− 0.028** (0.010)	− 0.002 (0.008)	0.001 (0.007)
Menu_i	− 0.001*** (0.000)	− 0.001*** (0.000)	0.001*** (0.000)
SameState_{ijt}	0.054*** (0.007)	0.031*** (0.005)	− 0.022*** (0.004)
Constant	6.170*** (0.056)	2.596*** (0.041)	1.436*** (0.035)
Restaurant fixed effect	Included	Included	Included
Time fixed effect	Included	Included	Included
Site fixed effect	Included	Included	Included
R^2	0.067	0.028	0.050

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Robust standard errors in parentheses

in subsequent review length. However, its impact on the other linguistic features was insignificant. These features include words reflecting cognitive or affective mental processes ($\ln(\text{CognitiveLang}_{ijt})$, $\ln(\text{AffectiveLang}_{ijt})$). Row 2 depicts the impact of review response diversity on the linguistic features of subsequent reviews. The results show that diversity positively affects subsequent review length and cognitive language, supporting H2. Based on the coefficients, a 1% increase in review response diversity results in a 1.79% increase in the subsequent review length and a 0.83% increase in the cognitive process language contained in subsequent reviews. That is, providing diverse feedback tailored to the content of each review encourages subsequent reviewers to share more personal experiences with logical articulation. The third row illustrates the impact of review-response similarity on subsequent review characteristics; specifically, the similarity has a positive impact on the affective language used in subsequent reviews, supporting H3. According to the analysis, a 1% increase in the textual similarity of responses and the corresponding review results in a 39.61% increase in the number of affective words in subsequent reviews. This result indicates that an increase in the number of tailored responses using similar wording to reviews contributes to a rise in the use of affective words such as “happy”, “sad,” or “annoyed” in subsequent reviews.

Figure 5 shows the marginal effects plots for the results of the hypotheses. The graph indicates that the impact of response intensity and diversity on subsequent review length, response diversity on the amount of cognitive language in subsequent reviews, and review-response similarity on the amount of affective language in subsequent reviews are significantly positive. The shaded area represents the

95% confidence interval, indicating the significance of the effects of each independent variable on the dependent variable. The slope of the line indicates the effect size, corresponding to the coefficients in the results tables. The first graph shows the impact of response intensity on subsequent review length. The graph shows a second gentler slope, indicating the second smallest effect size as shown by the coefficient (0.009) in Table 5. The finding indicates that as the business owner increases the frequency of their responses, subsequent reviewers are more likely to provide longer reviews. For instance, if a restaurant owner responded to 100 out of 1000 reviews and increases response intensity by 1%, resulting in 101 responses to reviews, the length of subsequent reviews will increase by about 0.94%. This implies that the review space, once considered a unilateral channel of information sharing, is now recognized as a conversational community that encourages users to provide more information.

The second and third graphs illustrate the results for H2, which examine the impact of response diversity on subsequent review length and the amount of cognitive language used in subsequent reviews. The slope of the second graph shows the second steepest slope, showing the second largest effect size as shown by the coefficient (0.018) in Table 4. The third graph represents the impact of response diversity on cognitive language in subsequent reviews. It has the gentlest slope compared to the other graphs in Fig. 5, indicating the least effect size, represented by the smallest coefficient (0.008) in Table 5. These results imply that response diversity increases the quantity and quality of information in a review. That is, while the second graph reveals how business owners’ varying responses enhance the volume of information, the third graph demonstrates that it also enhances the

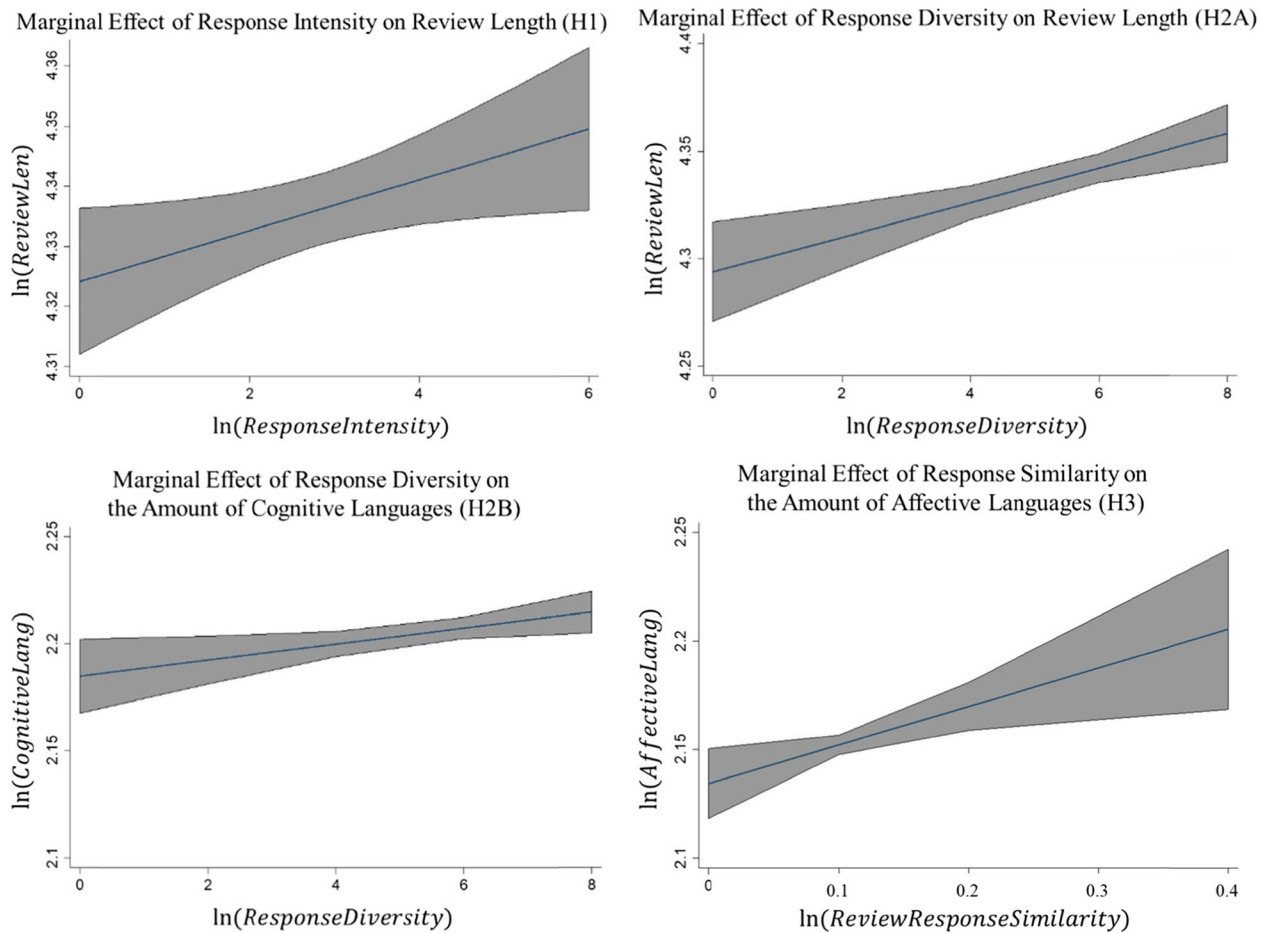


Fig. 5 Marginal effect plots of the hypothesized results

informativeness of the review space. The last graph illustrates the impact of review response similarity on the affective language used in subsequent reviews. It contains the steepest line, visualizing the most significant effect size, represented by the largest coefficient (0.396) in Table 4. Notably, the effect size of review-response similarity appears substantially larger, indicating that the primary function of review responses is to enhance service quality and encourage customer revisits. Moreover, reviews can be understood not merely as means to convey information, but also as a way to express experiences and perceptions of a service or product.

Discussion

This study examines the effect of changes in review space dynamics resulting from strategic review responses on the linguistic features of subsequent reviews, using an empirical analysis of data from Yelp and TripAdvisor. The DID analysis shows that review response characteristics of the review space, such as response intensity, response diversity,

and review-response similarity, affect subsequent reviews, thereby changing the overall characteristics of review spaces. As the number of responses increases, the subsequent review text lengthens, increasing its helpfulness. Responses that differ by review may indicate that businesses are attempting to be responsive to each reviewer's needs, resulting in subsequent reviews that contain more information, longer text, and increased cognitive language. When responses use similar words to those in reviews, it signals that relationship-building efforts are the norm, motivating reviewers to make comparable efforts in their writing, resulting in reviews that contain more affective language.

Moreover, we found several interesting additional findings through DID analysis. The increased intensity of responses in the review space only impacted the length of subsequent reviews, but response diversity positively affected both the length of subsequent reviews and the use of cognitive words. However, response diversity in the review space decreased the use of affective language in subsequent reviews (a 1% increase in response diversity resulted in a 0.74% decrease in the number of affective words in subsequent reviews).

Interestingly, review-response similarity decreased the length of subsequent reviews (a 1% increase in review-response similarity decreased the length of subsequent reviews by 73.62%), while increasing affective language in subsequent reviews. These results suggest that response diversity and review-response similarity may create different atmospheres in review spaces. When responses vary by review, it signals that a responder is trying to accommodate the diverse needs of reviewers, demonstrating that comments are highly scrutinized and responded to; thus, lengthy cognitive texts expressing detailed concerns and opinions may be generated. In contrast, when responses repeat the reviewer's words, it may hint that responders are mirroring language to communicate in a more affective way, as mirroring is an emotional approach for fostering closeness in relationships (Pickering & Garrod, 2004). If brief communication is expected based on the previous reviews and responses, the subsequent reviews may follow this communication form.

We also identify the rationale behind this shift in review space through the lens of social presence theory. The change in the number of cognitive or affective words used by a communicator is one of the interesting consequences of social presence (Huang et al., 2017). When a reviewer expresses their emotions in a review (e.g., words like 'happy,' 'sad,' or 'fun'), they are less likely to express their cognitive process (e.g., words like 'because,' 'not,' or 'make'), and vice versa. Affective and cognitive processes are usually regarded as opposing, suggesting that when individuals draw upon one, they do not rely on the other (Shiv & Fedorikhin, 1999). This may explain our analysis results, which show that affective language decreases when cognitive language increases under response diversity. In summary, the findings suggest that the presence and characteristics of review responses indeed change review space dynamics. Furthermore, social presence can explain the changes in reviewers' writing behaviors.

Limitations and future research opportunities

This study's findings have some limitations. First, as we only focused on one review type (i.e., restaurant reviews), the interpretation of the results should consider this particular review space, which encompasses both product (food) and service information. Therefore, examining product or service review spaces separately may engender different results. Future researchers should consider applying the findings of this study to multiple review spaces to enhance their knowledge on this topic.

Second, our analysis only focused on restaurants in the USA. As cultural background may affect communication style, future studies can enrich our findings by considering restaurants in different countries.

Third, we only examined the linguistic features of reviews but did not scrutinize the actual changes in the content of review topics. With the help of machine learning, such as topic modelling, future studies can expand the findings of our study by examining how the content changes.

Finally, we measured affective and cognitive language and discussed their informational and relational contribution to review spaces. Although previous literature suggests that affective and cognitive language represent informational or relational content, they are still proxies that do not directly measure information or the relational change of review spaces. Thus, caution is required when determining whether a review space is informational or relational. Future studies should develop information and relational indices that directly measure the characteristics of review spaces, utilizing text mining and machine learning to address both the linguistics and semantics of the text. These studies should also explicitly investigate review space quality in terms of informative and relationship values.

Managerial implications

Our study provides certain guidance for managers to implement in practice. First, the findings of this study have immediate implications for firm administrators who wish to manage online reviews. According to this study's findings, managers can consider two strategy types depending on their business stage. If they are in the initial stage and are introducing new products or services to attract new customers, they may benefit from a review space that contains substantial information that potential consumers may find useful. In this case, managers should leave many varied responses using cognitive language. However, if firms are experiencing a weak brand image, reduced customer loyalty, or low repurchase rates, then customer relationship management is needed. Thus, managers may consider adopting response language similar to that in reviews.

Note that using these two response strategies requires caution, as review-response similarity contributes to shortening subsequent review length, which may be unhelpful in constructing informative review spaces. As this study's findings suggest, review-response similarity reduces the length of subsequent reviews, while the cognitive language induced by response diversity decreases affective language in those reviews. Therefore, managers should carefully determine which strategy to implement. What may be optimal is using a response diversity strategy with cognitive language when introducing products and services, and then waiting for the review space to become more informative. If products and services enter the mature stage, which requires customers to be emotionally supported rather than receive well-known product information, switching to a strategy of increasing

review-response similarity with affective language may be more helpful.

Second, new types of marketing channels have emerged in online communication platforms. For instance, influencers have become prevalent with the growth of social media, and influencer marketing can be used to sell products based on consumers' recognition of influencers. In this context, online communication is a critical marketing strategy. As a new type of manager, how do influencers' responses to their "followers" (i.e., the customers) affect their marketing performance? In this respect, this study offers insights to managers whose communication skills are crucial in today's diverse marketing environments.

Third, the application of our findings can be extended to environments similar to review spaces, such as news comment spaces. Professional moderators who utilize replies and counter-speech can leverage our findings to address malicious comments and foster healthy discussion. However, previous research has suggested that comments made by moderators are less effective than those made by other users (Naab et al., 2020). This may be because moderator comments cannot directly address or mitigate the hate and uncivil behavior of commenters. However, our findings suggest that if a moderator carefully chooses their words, the entire review space may change over time. For example, if a moderator varies their responses using cognitive language, accurate information can override fake information; however, if a moderator adopts similar language to commenters, particularly by using affective language, reviewers may recognize that there is a person who reads and cares about their comments. Again, this may not immediately change reviewers' behaviors, but could shift the characteristics of the review space over time, subtly nudging the comment space to move in a more positive direction.

Theoretical implications

This study's findings provide several theoretical implications. First, an immediate implication is that the results can enrich our knowledge of marketing communication. This finding aligns with the results of previous studies, which suggest that utilizing linguistic features as specific response strategies can enhance customer engagement and satisfaction, as well as improve business performance (Han et al., 2023; Ren et al., 2024; Xu & Zhao, 2022). Particularly, by examining specific response strategies characterized by varying linguistic features, we explicitly show how managers' communications with reviewers can change the length and language of subsequent reviews, helping to increase customer engagement through manager responsiveness.

Second, moving beyond responses as a strategy, which has been the focus of existing marketing communication literature, our findings consider the entire review space,

suggesting that a review response can indeed affect the dynamics of the entire space (Hung et al., 2024). Review responses were not part of the original concept of a review space, as it was initially considered that the existence of a person (or a business) directly involved as the target of reviews might disturb the free expression of opinions. Thus, our study attempts to understand the dynamic change in the review space following this intervention. The findings suggest that managers' involvement can change the review space by influencing the linguistic characteristics of subsequent responses. While the actions and their outcomes may be similar, changing our focus from marketing communications and customer performance metrics to the effects of responders' interventions in online dynamics can enhance our understanding of collective behaviors in different digital environments. This shift can also broaden the interpretation and usage of the related phenomena. Possible issues resulting from this application include determining who responds to what and how responses should be formulated. For example, to enhance deliberative democracy and prevent malicious comments, professional moderators can be employed to address harmful speech in reviews. Our findings suggest that when moderation is applied thoughtfully, the dynamics of the review space can become more cognitively engaging and emotionally resonant.

Third, we present social presence as the driving mechanism behind the dynamic change in the online review space. As social presence clarifies how people perceive their social surroundings and behave, it provides an appropriate lens to view the dynamic changes in online review spaces.

Fourth, we integrated and synthesized the previous literature, finding three essential decisions to make when tailoring responses: (1) the frequency of responses (Sheng et al., 2021), (2) the degree of response variation (Li et al., 2018; Liu et al., 2021; Lopez-Lopez et al., 2025; Wu et al., *in press*), and (3) the degree of a response's resemblance to the corresponding review (Darani et al., 2023; Deng & Ravichandran, 2024; Ren et al., 2024; Zhou et al., 2023). These decisions also relate to which components of the review space to focus on, such as actors, reviews, or responses. To integrate previous literature, we examined all three tailoring decisions, represented as response intensity, response diversity, and review-response similarity. This approach can serve as a base framework for future studies in tailoring response strategies.

Fifth, another potential issue arises due to large language models (LLMs), which can automatically generate review responses. While LLMs make responding easier and faster, they may cause responses to lack a "human touch," such as spontaneity or sincerity. In this case, researchers should shift their focus from merely examining how responsiveness influences review content to exploring how the review space itself is transformed. Our findings show that by just

varying linguistic characteristics, which LLMs can easily do, the atmosphere of the review space can be altered, leading to a shift in reviewer behavior. Therefore, understanding the reviews and responses from the perspective of changes in review space dynamics, as suggested in our study, can expand future studies on online reviews.

Acknowledgements This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2019S1A5A2A03041910). Jinyoung Min is the corresponding author.

Funding Open Access funding enabled and organized by Chung-Ang University.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal Of Economics*, 119(1), 249–275. <https://doi.org/10.1162/003355304772839588>
- Callaway, B., Goodman-Bacon, A., & Sant'Anna, P. H. (2024). *Difference-in-differences with a continuous treatment* (No. w32117). National Bureau of Economic Research NBER Working Paper. <https://doi.org/10.3386/w32117>
- Chan, J. Y.-L., Leow, S. M. H., Bea, K. T., Cheng, W. K., Phoong, S. W., Hong, Z.-W., & Chen, Y.-L. (2022). Mitigating the multicollinearity problem and its machine learning approach: A review. *Mathematics*, 10(8), 1283. <https://doi.org/10.3390/math10081283>
- Chen, W., Gu, B., Ye, Q., & Zhu, K. X. (2019). Measuring and managing the externality of managerial responses to online customer reviews. *Information Systems Research*, 30(1), 81–96. <https://doi.org/10.1287/isre.2018.0781>
- Cheung, C. M., Xiao, B. S., & Liu, I. L. (2014). Do actions speak louder than voices? The signaling role of social information cues in influencing consumer purchase decisions. *Decision Support Systems*, 65, 50–58. <https://doi.org/10.1016/j.dss.2014.05.002>
- Chevalier, J. A., Dover, Y., & Mayzlin, D. (2018). Channels of impact: User reviews when quality is dynamic and managers respond. *Marketing Science*, 37(5), 688–709. <https://doi.org/10.1287/mksc.2018.1090>
- Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal Of Marketing Research*, 43(3), 345–354. <https://doi.org/10.1509/jmkr.43.3.345>
- Choi, H. S., Oh, W., Kwak, C., Lee, J., & Lee, H. (2022). Effects of online crowds on self-disclosure behaviors in online reviews: A multidimensional examination. *Journal of Management Information Systems*, 39(1), 218–246. <https://doi.org/10.1080/07421222.2021.2023412>
- Chua, A. Y., & Banerjee, S. (2015). Understanding review helpfulness as a function of reviewer reputation, review rating, and review depth. *Journal of the Association for Information Science and Technology*, 66(2), 354–362. <https://doi.org/10.1002/asi.23180>
- Cyr, D., Hassanein, K., Head, M., & Ivanov, A. (2007). The role of social presence in establishing loyalty in e-service environments. *Interacting with Computers*, 19(1), 43–56. <https://doi.org/10.1016/j.intcom.2006.07.010>
- Darani, M. M., Mirahmad, H., Raoofpanah, I., & Groening, C. (2023). Managerial responses to online communication: The role of mimicry in affecting third-party observers' purchase intentions. *Journal of Business Research*, 166, Article 113979. <https://doi.org/10.1016/j.jbusres.2023.113979>
- Deng, C., & Ravichandran, T. (2024). Managerial response to online positive reviews: Helpful or harmful? *Information Systems Research*, 35(4), 1802–1823. <https://doi.org/10.1287/isre.2019.0175>
- Derks, D., Fischer, A. H., & Bos, A. E. (2008). The role of emotion in computer-mediated communication: A review. *Computers in Human Behavior*, 24(3), 766–785. <https://doi.org/10.1016/j.chb.2007.04.004>
- Dickinger, A., & Bauernfeind, U. (2009). An analysis of corporate e-mail communication as part of airlines' service recovery strategy. *Journal of Travel & Tourism Marketing*, 26(2), 156–168. <https://doi.org/10.1080/10548400902864651>
- Fan, W., Liu, Y., Li, H., Tuunainen, V. K., & Lin, Y. (2022). Quantifying the effects of online review content structures on hotel review helpfulness. *Internet Research*, 32(7), 202–227. <https://doi.org/10.1108/INTR-11-2019-0452>
- Flanagin, A. J. (2017). Online social influence and the convergence of mass and interpersonal communication. *Human Communication Research*, 43(4), 450–463. <https://doi.org/10.1111/hcre.12116>
- Garaus, M., Wagner, U., & Kummer, C. (2015). Cognitive fit, retail shopper confusion, and shopping value: Empirical investigation. *Journal of Business Research*, 68(5), 1003–1011. <https://doi.org/10.1016/j.jbusres.2014.10.002>
- Gillespie, B., Muehling, D. D., & Kareklas, I. (2018). Fitting product placements: Affective fit and cognitive fit as determinants of consumer evaluations of placed brands. *Journal of Business Research*, 82, 90–102. <https://doi.org/10.1016/j.jbusres.2017.09.002>
- Greifeneder, R., Bless, H., & Pham, M. T. (2011). When do people rely on affective and cognitive feelings in judgment? A review. *Personality and Social Psychology Review*, 15(2), 107–141. <https://doi.org/10.1177/1088868310367640>
- Grewal, L., & Stephen, A. T. (2019). In mobile we trust: The effects of mobile versus nonmobile reviews on consumer purchase intentions. *Journal of Marketing Research*, 56(5), 791–808. <https://doi.org/10.1177/0022243719834514>
- Han, S., Anderson, C. K., & Chung, K. (2023). Do managerial communications improve customer satisfaction and eWOM? The moderating effect of response authenticity. *Humanities and Social Sciences Communications*, 10(1), 1–12. <https://doi.org/10.1057/s41599-023-01979-2>
- Hess, T. J., Fuller, M., & Campbell, D. E. (2009). Designing interfaces with social presence: Using vividness and extraversion to create social recommendation agents. *Journal of the Association for Information Systems*. <https://doi.org/10.17705/1jais.00216>
- Hou, J., & Ma, X. (2022). Space norms for constructing quality reviews on online consumer review sites. *Information Systems Research*, 33(3), 1093–1112. <https://doi.org/10.1287/isre.2022.1102>
- Huang, N., Hong, Y., & Burtch, G. (2017). Social network integration and user content generation: Evidence from natural experiments. *MIS Quarterly*, 41(4), 1035–1058. <https://doi.org/10.25300/MISQ/2017/41.4.02>
- Hung, H.-Y., Hu, Y., Lee, N., & Tsai, H.-T. (2024). Exploring online consumer review-management response dynamics: A

- heuristic-systematic perspective. *Decision Support Systems*, 177, Article 114087. <https://doi.org/10.1016/j.dss.2023.114087>
- Jackson, T. W., & Farzaneh, P. (2012). Theory-based model of factors affecting information overload. *International Journal of Information Management*, 32(6), 523–532. <https://doi.org/10.1016/j.ijinfomgt.2012.04.006>
- Jiang, G., Liu, F., Liu, W., Liu, S., Chen, Y., & Xu, D. (2021). Effects of information quality on information adoption on social media review platforms: Moderating role of perceived risk. *Data Science And Management*, 1(1), 13–22. <https://doi.org/10.1016/j.dsm.2021.02.004>
- Jin, W., Chen, Y., Yang, S., Zhou, S., Jiang, H., & Wei, J. (2023). Personalized managerial response and negative inconsistent review helpfulness: The mediating effect of perceived response helpfulness. *Journal of Retailing and Consumer Services*, 74, Article 103398. <https://doi.org/10.1016/j.jretconser.2023.103398>
- Kopp, T., Riekert, M., & Utz, S. (2018). When cognitive fit outweighs cognitive load: Redundant data labels in charts increase accuracy and speed of information extraction. *Computers in Human Behavior*, 86, 367–376. <https://doi.org/10.1016/j.chb.2018.04.037>
- Kou, Y., Powpaka, S., Zhou, L., Huang, J., & Lu, D. (2025). User presence in online product reviews: The dual effects on purchase intention. *Journal of Business Research*, 199, Article 115563. <https://doi.org/10.1016/j.jbusres.2025.115563>
- Ku, C.-H., Chang, Y.-C., & Wang, Y. (2024). How to strategically respond to online hotel reviews: A strategy-aware deep learning approach. *Information and Management*, 61(5), Article 103970. <https://doi.org/10.1016/j.im.2024.103970>
- Kumar, N., Qiu, L., & Kumar, S. (2018). Exit, voice, and response on digital platforms: An empirical investigation of online management response strategies. *Information Systems Research*, 29(4), 849–870. <https://doi.org/10.1287/isre.2017.0749>
- Kwok, L., & Xie, K. L. (2016). Factors contributing to the helpfulness of online hotel reviews: Does manager response play a role? *International Journal of Contemporary Hospitality Management*, 28(10), 2156–2177. <https://doi.org/10.1108/IJCHM-03-2015-0107>
- Lee, H. A., Choi, A. A., Sun, T., & Oh, W. (2021). Reviewing before reading? An empirical investigation of book-consumption patterns and their effects on reviews and sales. *Information Systems Research*, 32(4), 1368–1389. <https://doi.org/10.1287/isre.2021.1029>
- Li, C., Cui, G., & Peng, L. (2017). The signaling effect of management response in engaging customers: A study of the hotel industry. *Tourism Management*, 62, 42–53. <https://doi.org/10.1016/j.tourman.2017.03.009>
- Li, C., Cui, G., & Peng, L. (2018). Tailoring management response to negative reviews: The effectiveness of accommodative versus defensive responses. *Computers in Human Behavior*, 84, 272–284. <https://doi.org/10.1016/j.chb.2018.03.009>
- Li, M., & Huang, P. (2020). Assessing the product review helpfulness: Affective-cognitive evaluation and the moderating effect of feedback mechanism. *Information and Management*, 57(7), Article 103359. <https://doi.org/10.1016/j.im.2020.103359>
- Li, X., & Hitt, L. M. (2008). Self-selection and information role of online product reviews. *Information Systems Research*, 19(4), 456–474. <https://doi.org/10.1287/isre.1070.0154>
- Liu, S., Wang, N., Gao, B., & Gallivan, M. (2021). To be similar or to be different? The effect of hotel managers' rote response on subsequent reviews. *Tourism Management*, 86, Article 104346. <https://doi.org/10.1016/j.tourman.2021.104346>
- Lopes, A. I., Dens, N., De Pelsmacker, P., & Malthouse, E. C. (2023). Managerial response strategies to eWOM: A framework and research agenda for webcare. *Tourism Management*, 98, Article 104739. <https://doi.org/10.1016/j.tourman.2023.104739>
- Lopez-Lopez, D., Plaza-Navas, M. A., Torres-Pruñonosa, J., & Martinez, L. F. (2025). Navigating the landscape of e-commerce: Thematic clusters, intellectual turning points, and burst patterns in online reputation management. *Electronic Commerce Research*, 25(1), 1–38. <https://doi.org/10.1007/s10660-024-09893-8>
- Lutz, B., Pröllochs, N., & Neumann, D. (2022). Are longer reviews always more helpful? Disentangling the interplay between review length and line of argumentation. *Journal of Business Research*, 144, 888–901. <https://doi.org/10.1016/j.jbusres.2022.02.010>
- Mackiewicz, J., & Yeats, D. (2014). Product review users' perceptions of review quality: The role of credibility, informativeness, and readability. *IEEE Transactions on Professional Communication*, 57(4), 309–324. <https://doi.org/10.1109/TPC.2014.2373891>
- Mauri, A. G., & Minazzi, R. (2013). Web reviews influence on expectations and purchasing intentions of hotel potential customers. *International Journal of Hospitality Management*, 34, 99–107. <https://doi.org/10.1016/j.ijhm.2013.02.012>
- McMains, M. J., & Lanceley, F. J. (2003). The use of crisis intervention principles by police negotiators. *Journal of Police Crisis Negotiations*, 3(1), 3–30. https://doi.org/10.1300/J173v03n01_02
- Molinillo, S., Aguilar-Illescas, R., Anaya-Sánchez, R., & Vallespín-Arán, M. (2018). Exploring the impacts of interactions, social presence and emotional engagement on active collaborative learning in a social web-based environment. *Computers & Education*, 123, 41–52. <https://doi.org/10.1016/j.compedu.2018.04.012>
- Moore, S. G., & Lafreniere, K. C. (2020). How online word-of-mouth impacts receivers. *Consumer Psychology Review*, 3(1), 34–59. <https://doi.org/10.1002/arcp.1055>
- Mudambi, S. M., & Schuff, D. (2010). Research note: What makes a helpful online review? A Study of customer reviews on Amazon.com. *MIS Quarterly*, 34(1), 185–200. <https://doi.org/10.2307/20721420>
- Naab, T. K., Heinbach, D., Ziegele, M., & Grasberger, M.-T. (2020). Comments and credibility: How critical user comments decrease perceived news article credibility. *Journalism Studies*, 21(6), 783–801. <https://doi.org/10.1080/1461670X.2020.1724181>
- Palese, B., Piccoli, G., & Lui, T.-W. (2021). Effective use of online review systems: Congruent managerial responses and firm competitive performance. *International Journal of Hospitality Management*, 96, Article 102976. <https://doi.org/10.1016/j.ijhm.2021.102976>
- Pan, Y., & Zhang, J. Q. (2011). Born unequal: A study of the helpfulness of user-generated product reviews. *Journal of Retailing*, 87(4), 598–612. <https://doi.org/10.1016/j.jretai.2011.05.002>
- Park, S. K., Song, T., & Sela, A. (2023). The effect of subjectivity and objectivity in online reviews: A convolutional neural network approach. *Journal of Consumer Psychology*, 33(4), 701–713. <https://doi.org/10.1002/jcpsy.1382>
- Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015). *The development and psychometric properties of LIWC2015*. University of Texas at Austin. <http://hdl.handle.net/2152/31333>
- Pickering, M. J., & Garrod, S. (2004). Toward a mechanistic psychology of dialogue. *Behavioral And Brain Sciences*, 27(2), 169–190. <https://doi.org/10.1017/S0140525X04000056>
- Proserpio, D., & Zervas, G. (2017). Online reputation management: Estimating the impact of management responses on consumer reviews. *Marketing Science*, 36(5), 645–665. <https://doi.org/10.1287/mksc.2017.1043>
- Pu, J., Chen, Y., Qiu, L., & Cheng, H. K. (2020). Does identity disclosure help or hurt user content generation? Social presence, inhibition, and displacement effects. *Information Systems Research*, 31(2), 297–322. <https://doi.org/10.1287/isre.2019.0885>
- Qian, Y., Ni, Z., Zheng, H., Liu, Z., & Ma, F. (2023). Factors influencing users' post replying behavior in a senior online community: An empirical investigation. *Telematics and Informatics*, 77, Article 101926. <https://doi.org/10.1016/j.tele.2022.101926>
- Rathjens, B., Van Der Heide, B., Pham, D., Earle, K., Ulusoy, E., Mason, A. J., Zhang, Y., & Bredland, A. (2023). Negative online

- reviews and manager response: Applying expectancy disconfirmation theory in a CMC context. *Communication Reports*, 36(2), 110–122. <https://doi.org/10.1080/08934215.2022.2154815>
- Ravichandran, T., & Deng, C. (2023). Effects of managerial response to negative reviews on future review valence and complaints. *Information Systems Research*, 34(1), 319–341. <https://doi.org/10.1287/isre.2022.1122>
- Ren, X., Wang, L., & Luo, X. R. (2024). How customized managerial responses influence subsequent consumer ratings: The language style matching perspective. *Decision Support Systems*, 180, Article 114188. <https://doi.org/10.1016/j.dss.2024.114188>
- Ruiz-Mafe, C., Chatzipanagiotou, K., & Curras-Perez, R. (2018). The role of emotions and conflicting online reviews on consumers' purchase intentions. *Journal Of Business Research*, 89, 336–344. <https://doi.org/10.1016/j.jbusres.2018.01.027>
- Shen, W., Hu, Y. J., & Ulmer, J. R. (2015). Competing for attention. *MIS Quarterly*, 39(3), 683–696. <https://www.jstor.org/stable/26629626>
- Sheng, J. (2019). Being active in online communications: Firm responsiveness and customer engagement behaviour. *Journal of Interactive Marketing*, 46, 40–51. <https://doi.org/10.1016/j.intmar.2018.11.004>
- Sheng, J., Wang, X., & Amankwah-Amoah, J. (2021). The value of firm engagement: How do ratings benefit from managerial responses? *Decision Support Systems*, 147, Article 113578. <https://doi.org/10.1016/j.dss.2021.113578>
- Shiv, B., & Fedorikhin, A. (1999). Heart and mind in conflict: The interplay of affect and cognition in consumer decision making. *Journal of Consumer Research*, 26(3), 278–292. <https://doi.org/10.1086/209563>
- Short, J., Williams, E., & Christie, B. (1976). *The social psychology of telecommunications*. Wiley.
- Sia, C.-L., Tan, B. C., & Wei, K.-K. (2002). Group polarization and computer-mediated communication: Effects of communication cues, social presence, and anonymity. *Information Systems Research*, 13(1), 70–90. <https://doi.org/10.1287/isre.13.1.70.92>
- Song, Y., & Tian, X. (2020). Managerial responses and customer engagement in crowdfunding. *Sustainability*, 12(8), Article 3389. <https://doi.org/10.3390/su12083389>
- Sparks, B. A., So, K. K. F., & Bradley, G. L. (2016). Responding to negative online reviews: The effects of hotel responses on customer inferences of trust and concern. *Tourism Management*, 53, 74–85. <https://doi.org/10.1016/j.tourman.2015.09.011>
- Srivastava, V., & Kalro, A. D. (2019). Enhancing the helpfulness of online consumer reviews: The role of latent (content) factors. *Journal of Interactive Marketing*, 48(1), 33–50. <https://doi.org/10.1016/j.intmar.2018.12.003>
- Sun, X., Han, M., & Feng, J. (2019). Helpfulness of online reviews: Examining review informativeness and classification thresholds by search products and experience products. *Decision Support Systems*, 124, Article 113099. <https://doi.org/10.1016/j.dss.2019.113099>
- Tan, K.P.-S., Liu, Y. V., & Litvin, S. W. (2025). ChatGPT and online service recovery: How potential customers react to managerial responses of negative reviews. *Tourism Management*, 107, Article 105057. <https://doi.org/10.1016/j.tourman.2024.105057>
- Tep, S. P., Aljukhadar, M., Sénécal, S., & Dantas, D. C. (2022). The impact of social features in an online community on member contribution. *Computers in Human Behavior*, 129, Article 107149. <https://doi.org/10.1016/j.chb.2021.107149>
- Vecchi, G. M., Van Hasselt, V. B., & Romano, S. J. (2005). Crisis (hostage) negotiation: Current strategies and issues in high-risk conflict resolution. *Aggression And Violent Behavior*, 10(5), 533–551. <https://doi.org/10.1016/j.avb.2004.10.001>
- Walther, J. B. (1996). Computer-mediated communication: Impersonal, interpersonal, and hyperpersonal interaction. *Communication Research*, 23(1), 3–43. <https://doi.org/10.1177/009365096023001001>
- Wang, F., Du, Z., & Wang, S. (2023). Information multidimensionality in online customer reviews. *Journal of Business Research*, 159, Article 113727. <https://doi.org/10.1016/j.jbusres.2023.113727>
- Wang, L., Ren, X., Wan, H., & Yan, J. (2020). Managerial responses to online reviews under budget constraints: Whom to target and how. *Information & Management*, 57(8), Article 103382. <https://doi.org/10.1016/j.im.2020.103382>
- Wang, Y., & Chaudhry, A. (2018). When and how managers' responses to online reviews affect subsequent reviews. *Journal of Marketing Research*, 55(2), 163–177. <https://doi.org/10.1509/jmr.15.0511>
- Wei, W., Miao, L., & Huang, Z. J. (2013). Customer engagement behaviors and hotel responses. *International Journal of Hospitality Management*, 33, 316–330. <https://doi.org/10.1016/j.ijhm.2012.10.002>
- Wu, J., Ye, J., & Chu, J. (in press). Soothing the unsatisfied or pleasing the satisfied? The effects of managerial responses to positive versus negative reviews on customer ratings and financial performance. *Journal of the Academy of Marketing Science*. <https://doi.org/10.1007/s11747-024-01010-3>
- Xie, K. L., Zhang, Z., & Zhang, Z. (2014). The business value of online consumer reviews and management response to hotel performance. *International Journal of Hospitality Management*, 43, 1–12. <https://doi.org/10.1016/j.ijhm.2014.07.007>
- Xu, X., & Zhao, Y. (2022). Examining the influence of linguistic characteristics of online managerial response on return customers' change in satisfaction with hotels. *International Journal of Hospitality Management*, 102, Article 103146. <https://doi.org/10.1016/j.ijhm.2022.103146>
- Xu, Y., Li, H., Law, R., & Zhang, Z. (2020). Can receiving managerial responses induce more user reviewing effort? A mixed method investigation in hotel industry. *Tourism Management*, 77, Article 103982. <https://doi.org/10.1016/j.tourman.2019.103982>
- Zhang, Z., Li, H., Meng, F., & Li, Y. (2019). The effect of management response similarity on online hotel booking: Field evidence from Expedia. *International Journal of Contemporary Hospitality Management*, 31(7), 2739–2758. <https://doi.org/10.1108/IJCHM-09-2018-0740>
- Zhang, X., Qiao, S., Yang, Y., & Zhang, Z. (2020). Exploring the impact of personalized management responses on tourists' satisfaction: A topic matching perspective. *Tourism Management*, 76, Article 103953. <https://doi.org/10.1016/j.tourman.2019.103953>
- Zhang, W., Wang, Q., Li, J., Ma, Z., Bhandari, G., & Peng, R. (2023). What makes deceptive online reviews? A linguistic analysis perspective. *Humanities and Social Sciences Communications*, 10, 769. <https://doi.org/10.1057/s41599-023-02295-5>
- Zhang, X., La, L., Huang, G. I., & Xie, H. (2024). Strategies and conditions for crafting managerial responses to online reviews. *Tourism Management*, 103, Article 104911. <https://doi.org/10.1016/j.tourman.2024.104911>
- Zhang, H., Xiang, Z., & Zach, F. J. (2025). Generative AI vs. humans in online hotel review management: A task-technology fit perspective. *Tourism Management*, 110, Article 105187. <https://doi.org/10.1016/j.tourman.2025.105187>
- Zhou, C., Yang, S., Chen, Y., Zhou, S., Li, Y., & Qazi, A. (2023). How does topic consistency affect online review helpfulness? The role of review emotional intensity. *Electronic Commerce Research*, 23(4), 2943–2978. <https://doi.org/10.1007/s10660-022-09597-x>
- Zhou, S., Qiao, Z., Du, Q., Wang, G. A., Fan, W., & Yan, X. (2018). Measuring customer agility from online reviews using big data text analytics. *Journal of Management Information Systems*, 35(2), 510–539. <https://doi.org/10.1080/07421222.2018.1451956>