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Style Matching or Content Matching? Moderating Role of Discrete Negative Emotions in the Effects of Managerial Responses Tailoring

Short Paper

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Abstract

Many firms are struggling with how to tailor their responses to online reviews expressing negative emotions. While most studies on the managerial response (MR) tailoring point to the importance of MR content, how the content is conveyed, often referred to as language style, has been underexplored. Drawing on the verbal mimicry and communication tailoring literature, we propose that style matching may be at least as important as content matching and play a different role when responding to reviews embedded with negative emotions. Further, we consider the differences among the various negative emotions expressed in reviews and explore how to tailor MR for reviews embedded with discrete negative emotions (anger, sadness, anxiety, and disgust) expressed in reviews. The results show that style matching is more effective for anger-embedded reviews and sadness-embedded reviews while content matching performs better for disgust-embedded reviews. However, these two tailoring strategies are not effective for anxiety-embedded reviews.

Keywords: Managerial response, discrete negative emotions, response tailoring, content matching, style matching

Introduction

Due to the long duration and the wide audience of online reviews, firms are under increasing pressure to maintain a good online reputation (Beverley et al., 2016; Kumar et al., 2018). In this case, it has become an increasingly common management strategy for firms to publicly respond to online reviews (i.e., managerial response, MR), which is supported by review platforms. However, many firms are struggling with how to respond to online reviews, especially negative reviews (e.g., Li et al., 2018). Research has long confirmed the existence of "negative bias", that is, negative reviews or experiences are more memorable, and thus have a greater impact on consumers than positive reviews (Rozin & Royzman, 2001; Beverley et al., 2016; Li et al., 2018). It has therefore been an important and urgent problem to explore how firms respond to reviews, especially how to tailor the response to reviews expressing negative emotions.

Prior literature on MR usually classifies online reviews into positive and negative reviews (e.g., Crijns et al., 2017; Huang et al., 2021; Wang & Chaudhry, 2018). Another fundamental theory of emotion is discrete emotion theory (e.g., Ekman, 1992). Discrete emotion theory identifies specific basic emotions that are prevalent in humans, such as happiness, expectation, sadness and anger. According to the cognitive appraisal theory of emotion and neuroimaging studies on emotion, discrete emotions are linked to discrete neural signals and certain structures of human brains and they are evoked by different cognitive appraisals (Lerner et al., 2015; Yu et al., 2023). These different cognitive appraisals include information such as problem-focused coping potential and emotion-focused coping potential which might influence the effects of different MR strategies (Lerner et al., 2015; Mccoll-Kennedy & Sparks, 2003; Yu et al., 2023). And thus, it is necessary to distinguish discrete emotions and study how different types of negative emotions expressed in reviews affect the effect of MR strategies.

Tailoring is a commonly used communication strategy in online communication including MR (Crijns et al., 2017; Huang et al., 2021; Wang & Chaudhry, 2018). While most studies on MR tailoring point to the importance of MR content (e.g., Huang et al., 2021; Wang & Chaudhry, 2018), the way the content is conveyed, often referred to as language style, has been underexplored (Zhang et al., 2020). As communication and verbal mimicry literature suggest, style matching and content matching are two fundamental and distinct tailoring strategies (e.g., Ireland & Pennebaker, 2010; Romero et al., 2015). In contrast to content matching focusing on content words such as nouns and verbs, style matching focuses on function words that do not contain semantic information and are the syntactic backbone of language (Gonzales et al., 2010). That is to say, while content matching focuses on what people say, style matching gives attention to how people say and is therefore inherently social (Romero et al., 2015), and related to positive affect and interpersonal liking in interactions (Niederhoffer & Pennebaker, 2002; Romero et al., 2015). And therefore, style matching may be at least as important as content matching and play a different role when responding to reviews embedded with different types of negative emotions.

Motivated by the above theoretical lens and practical problems, our study focuses on the following research question: How do the different basic types of discrete negative emotions (i.e., anger, sadness, anxiety, and disgust) expressed in reviews moderate the impact of different MR tailoring strategies (i.e., style matching and content matching) on customer satisfaction?

Our research questions are examined using data from one of the largest restaurant review platforms in China. To measure MR tailoring, we mainly use two text-mining techniques. The first is language style analysis, a word count-based language analytics approach that allows for the determination of how well the consumer review matches the MR in terms of style. The second method is based on topic modeling, a cosine coefficient of the angle between two topic distribution vectors in a vector space, which we use to measure the content matching between the consumer review and its matching MR. And following prior literature (e.g., Gu & Ye, 2014; Li et al., 2020), we use consumer rating to describe customer satisfaction. We mainly focus on four basic discrete negative emotions (i.e., anger, sadness, anxiety, and disgust). They are regarded as the most basic emotions that constitute other negative emotions, such as disappointment (Lerner et al., 2015; Yin et al., 2014; Yu et al., 2023). They are also the most common in online content (Quan & Ren, 2010; Yu et al., 2023). Our results show that not every type of response tailoring for negative reviews has positive effects and it is necessary to distinguish different types of discrete negative emotions. Specifically, style matching is more effective for anger-embedded reviews and sadness-embedded reviews while content matching performs better for anxiety-embedded reviews and disgust-embedded reviews.

Literature Review

Style Matching and Content Matching

The contrast between language content and style is crucial in the study of verbal mimicry and communication tailoring (e.g., Ireland & Pennebaker, 2010; Romero et al., 2015). The fundamental information that is communicated—what people say—is referred to as a text's content. Nouns, regular verbs, and a large number of adjectives and adverbs make up language content at the word level (e.g., Ireland & Pennebaker, 2010). By contrast, a measure of Language Style Matching (LSM) has been created by researchers to capture the process of accommodation and alignment (e.g., Romero et al., 2015). The fact that words that represent the style rather than the content of an utterance are predictive language components forms the basis of the LSM measure (Pennebaker, 2001; Romero et al., 2015).

Language style describes the manner in which information is expressed—how something is said (e.g., Ireland & Pennebaker, 2010; Romero et al., 2015). Style words, also referred to as function words, are the structural foundation of language and do not provide semantic information (Gonzales et al., 2010). Prepositions, conjunctions, articles, and other parts of speech without substance are included in the categories of function words (Gonzales et al., 2010; Ireland & Pennebaker, 2010). Style matching suggests that conversation partners are listening to one another on a fundamental level and can foster positive affect and interpersonal liking in interactions, in contrast to content matching (Niederhoffer & Pennebaker, 2002; Romero et al., 2015), which focuses on semantic content and implies that people are actively acting in a way to advance the conversation (Ireland & Pennebaker, 2010). For example, Ireland and Pennebaker (2010) explored style matching and content matching in everyday writing tasks and professional writing, and found these two matchings might play different roles, such as judges' ratings of similarity were related to content matching but not style matching.

The Effects of MR Tailoring

This paper mainly focuses on the literature examining the effects of MR tailoring. MR tailoring refers to the practice of customizing MR to the contents of the corresponding review (Huang et al., 2021; Wang & Chaudhry, 2018), emphasizing the dialogue and interaction between firms and consumers (Crijns et al., 2017). Prior literature has studied the interaction effect of MR tailoring and other factors especially review valence (Crijns et al., 2017; Huang et al., 2021; Wang & Chaudhry, 2018; Zhang et al., 2020). Most of these studies used consumer ratings or text sentiment analysis to divide reviews into positive and negative reviews and then studied the effects of MR tailoring (Crijns et al., 2017; Huang et al., 2021; Wang & Chaudhry, 2018). For example, Wang and Chaudhry (2018) used online review data from various popular travel websites and considered reviews with a score of 3 or less on a five-point scale to be negative reviews, and they discovered that MR to negative reviews can improve customer satisfaction, with response-tailoring strategies amplifying this positive impact. Li et al. (2018) analyzed the sentiment of reviews based on Linguistic Inquiry and Word Count (LIWC, Pennebaker et al., 2001) to identify negative reviews and discovered that semantically tailoring management responses to negative reviews can lead to better hotel sales.

The Effect of Emotions in Online Reviews Context

Existing research on online reviews and MR has mainly focused on valence analysis based on dimensional emotion theory (e.g., Wang & Chaudhry, 2018). However, valence is merely one of the important dimensions of human emotions (Lerner et al., 2015), and lab experiments show that valence-based predictions of consumer cognition and intention yield contradictory results (Yin et al., 2014; Yu et al., 2023). In view of discrete emotion theory, more recent related research has focused on different effects of discrete emotions (e.g., Li et al., 2020; Yin et al., 2014; Yu et al., 2023). Most of these studies focus on the impact of discrete emotions expressed in reviews on perceived review helpfulness and purchase intention. Only a few studies have considered the impact of discrete emotions expressed in reviews on the effect of MR (Li et al., 2020). For example, Li et al. (2020) focused on anxiety and anger expressed in reviews and studied how these two moderate the effects of MR content linguistic features on the next consumers observing them.

Literature Summaries

Prior literature on MR to negative reviews still lags in three aspects. First, the previous literature on MR especially MR tailoring has rarely considered the impact of discrete emotions expressed in reviews (Li et al., 2020). However, based on discrete emotion theory and cognitive appraisal theory of emotion, different types of negative emotions in reviews are related to different cognitive appraisals. And these cognitive appraisals such as problem-focused coping potential and emotion-focused coping potential might also influence the effects of different MR strategies. Second, while prior research on MR tailoring has generally focused on content matching, style matching may also play an important but distinct role but has been underexplored. Third, the previous literature on MR tailoring using secondary data was mainly studied at the firm level (e.g., Huang et al., 2021) while limited research has studied at an individual level (Wang & Chaudhry, 2018). However, research at an individual level can analyze the effect of MR on different consumers, especially consumers with negative emotions.

Hypothesis Development

Based on the cognitive appraisal theory of emotion and linguistic literature on tailoring, we propose how four basic types of discrete negative emotions (i.e., anger, sadness, anxiety, and disgust) expressed in reviews moderate the impact of two basic types of MR tailoring (i.e., style matching and content matching) on customer satisfaction. The two basic types of MR tailoring could improve customer satisfaction by providing support for negative emotions appeasing and problem coping, respectively. Specifically, style matching could signal that the firm is listening to them and taking their perspectives (Ireland & Pennebaker, 2010), providing potential support for negative emotions appeasing. Content matching focus on the semantic content such as the exact issues the consumer experienced in the reviews (Wang et al., 2018), providing potential support for problem coping.

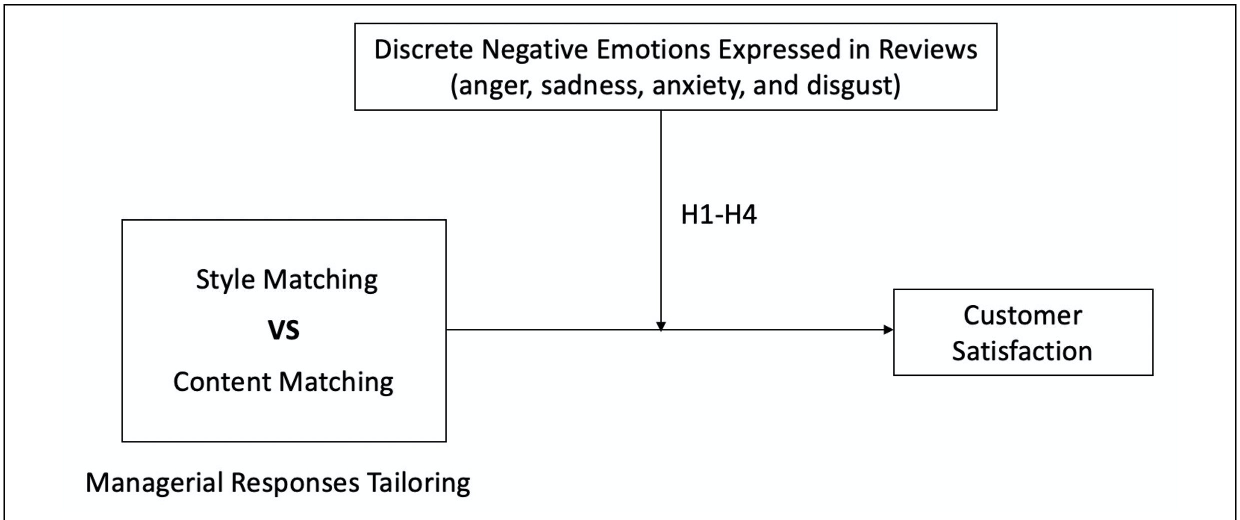

Figure 1. Research Model

Moderating Effects of Anger and Sadness

The core relational theme of anger is other blame (Smith & Lazarus, 1990). An archetypal emotional script for rage in a conventional setting might include: narrowing attention, speaking loudly, yelling, screaming, and verbally attacking the source (Yin et al., 2021). Moreover, angry actors are more likely to lack self-control and be unable to control their emotions, which impairs their ability to reason (Smith & Lazarus, 1990; Yin et al., 2021). That is to say, consumers leaving anger-embedded reviews might be irrational and unable to forward the issue and perceive gaining from responses even MRs with content matching are provided. By contrast, MRs with style matching will make consumers leaving anger-embedded reviews feel the firm is listening to them and taking their perspectives (Ireland & Pennebaker, 2010), relieving their feeling of other blame and even fostering positive affect (Niederhoffer & Pennebaker, 2002; Romero et al., 2015). In short, we hypothesize that:

H1. For anger-embedded reviews, MRs with higher style matching are more effective than MRs with higher content matching.

The core relational theme of sadness is irrevocable loss (Smith & Lazarus, 1990). Since people believe they lack the necessary ability or chance to act upon the situation to modify it in accordance with their desires and believe it is unlikely that the circumstances will change in a favorable way in the future, sadness is also linked to low problem-focused coping potential and low future expectancy (Lerner et al., 2015; Smith & Lazarus, 1990). That is to say, when firms provide MRs with content matching, consumers leaving sadness-embedded reviews will probably gain from the matching semantic content from response since they do not think they can cope with the situation and the circumstances might remain the same even with firms' potential solutions (Smith & Lazarus, 1990). By contrast, greater perspective-taking suggested by MRs with style matching might make consumers leaving sadness-embedded reviews feel heard (Ireland &

Pennebaker, 2010), and then help them cope with their negative emotions in a better way (Smith & Lazarus, 1990). In short, we hypothesize that:

H2. For sadness-embedded reviews, MRs with higher style matching are more effective than MRs with higher content matching.

Moderating Effects of Anxiety and Disgust

The core relational theme of anxiety is ambiguous threat (Smith & Lazarus, 1990). Since people might have a low perceived capacity to modify their own perceptions, beliefs, and/or desires about the event, anxiety is also linked to limited emotion-focused coping potential (Smith & Lazarus, 1990). That is to say, the effects of greater perspective-taking and potential emotional support from MRs with style matching might be limited since they may not think the firms will help them adjust their own perceptions about the negative event and cope with the negative emotions mentioned in reviews (Lerner et al., 2015; Smith & Lazarus, 1990). By contrast, consumers leaving anxiety-embedded reviews will not deny their ability or chance to act upon the situation to modify it in accordance with their desires. Further, MRs with content matching provided by firms focus on the semantic content usually containing exact issues the consumer experienced in the reviews, and then the matched semantic content in the MRs will probably include firms' potential solutions (e.g., Wang et al., 2018). Thus, the consumers might think they can gain help from the matching semantic content such as firms' potential solutions (e.g., Wang et al., 2018). In short, we hypothesize that:

H3. For anxiety-embedded reviews, MRs with higher content matching are more effective than MRs with higher style matching.

Disgust would appeal when people perceive someone as intentionally harming them or someone they care about and think it is undesirable and unfair (Fischer et al., 2018). Prior literature suggests individuals leaving expressions of disgust usually compare their own circumstances with others due to the feeling of unfairness (Fischer et al., 2018). Applied to our context, consumers leaving disgust-embedded reviews will probably care more about whether their own circumstances will be improved. That is to say, those consumers might gain help from MRs with content matching which probably includes some useful information for the consumers such as firms' potential solutions. By contrast, the effects of greater perspective-taking and potential emotional support gained in interactions from MRs with style matching might be minimized since disgust is characterized by a strong unwillingness to attend to a person (Lerner et al., 2015). In short, we hypothesize that:

H4. For disgust-embedded reviews, MRs with higher content matching are more effective than MRs with higher style matching.

Model Specification

To quantify the impact of different MR tailoring strategies (i.e., style matching and content matching), we employ a panel data approach for customers who provide multiple reviews to the same restaurant. We try to control for heterogeneity across customers, restaurants, and time, identifying the impact of MR tailoring by comparing changes in customer review ratings of those who receive MR with different tailoring strategies:

$$\begin{aligned} Rating_{ijt} = {} & \beta_1 Rating_{ijt-1} + \beta_2 \boldsymbol{NegEmotion_{ij(t-1)}} + \beta_3 StyleMatching_{ij(t-1)} + \beta_4 ContentMatching_{ij(t-1)} \\ & + \beta_5 StyleMatching_{ij(t-1)} \times \boldsymbol{NegEmotion_{ij(t-1)}} + \beta_6 ContentMatching_{ij(t-1)} \times \boldsymbol{NegEmotion_{ij(t-1)}} \\ & + \boldsymbol{\beta_7 ControlVars}_{ij(t-1)} + \theta_j + \theta_t + \epsilon_{ijt} \end{aligned} \quad (1)$$

$Rating_{ijt}$ is the rating given by customer i, which indicates his/her satisfaction with restaurant j at time t. $\boldsymbol{NegEmotion}_{ij(t-1)}$ is a four-dimensional vector representing the intensity of negative emotions for customer i with restaurant j at time t-1, consisting of the intensity of anger ($anger_{ij(t-1)}$), disgust ($disgust_{ij(t-1)}$), anxiety ($anxiety_{ij(t-1)}$), and sadness ($sadness_{ij(t-1)}$). To compute the intensity of discrete emotions for each review, we adopt the existing algorithms (Yu et al., 2023) and construct an emotional lexicon in the online restaurant review domain by extending a Chinese emotion lexicon, Ren-CECps (Quan & Ren, 2010). $StyleMatching_{ij(t-1)}$ and $ContentMatching_{ij(t-1)}$ represent the degree of style matching and content matching with regard to its matching review from customer i with restaurant *j* at time *t*, with scores closest to 1 reflecting a perfect match in style or content. To acquire style matching scores, the text of customer reviews and MRs was operationalized in steps using the LIWC dictionaries and get LSM measures (Pennebaker et al., 2001). Specifically, the LSM scores measuring the degree to which each text contained eight types of function words (e.g., adverbs, and personal pronouns) are we get the overall LSM score for a group of reviews and MRs by taking the average LSM score across all function words (see Pennebaker et al., 2001 for detail). To acquire content matching scores, latent Dirichlet allocation (LDA) was applied to the corpus of reviews and the matching responses, obtaining a mixture of topic distributions and assigning topic probabilities to each review or response (Wang & Chaudhry, 2018; Huang et al., 2021). And then we used the topic probability vectors of each review and the matching response to calculate the cosine similarity which indicates the content matching of MR.

In addition, the fixed effect θ_j and θ_t in the above equations identifies heterogeneity across restaurants and time, and the control variables $\boldsymbol{ControlVars}_{ij(t-1)}$ identify heterogeneity in customers (including the dummy indicating if the customer is a member, and the dummy indicating if the customer observed MR to other customers), review features (the average rating of the restaurant at the week to capture the average consumption experience, the intensity of all basic emotions to describe the specific consumption experience for the current visit, and log-transformed message length), and response (log-transformed message length, the speed of response, and the source of response).

One potential endogeneity issue is the sample selection bias since we can only regress on multi-visit customers when using ratings to describe customer satisfaction. The probability of consumers providing a subsequent review of the same restaurant may vary with style matching and content matching degrees of responses they receive, leading to a potential self-selection bias. To address this issue, we adopt the method described by Gu and Ye (2014), using Heckman's (1979) two-step approach. Specifically, in the first step, we model the probability of a review being selected using a Probit model based on response tailoring, and negative emotions in the review and the rating of last time. In addition, the restaurant dummy variables are added to the model to control for heterogeneity across restaurants in attracting customers to review again.

$$P\left(ReviewSelected_{ijt} = 1\right) = \Phi\left(ReviewSelected^*_{ijt} \geq 0\right) \quad (2)$$

$$ReviewSelected^*_{ijt} = \rho_1 StyleMatching_{ij(t-1)} + \rho_2 ContentMatching_{ij(t-1)} + \beta_\eta \eta_j + \epsilon_{ijt} \quad (3)$$

In the second step, we use the linear predicted value of $ReviewSelected^*_{ijt}$ from the Probit model to calculate the invert Mills ratio (IMR) for each review and include the ratio in the main models.

$$IMR_h = \lambda\left(-\overline{ReviewSelected^*_{ijt}}\right) \quad (4)$$

Preliminary Results

We collected data from 21,797 consumers who have provided reviews of 76 restaurants from 2010 to 2019 on one of the largest restaurant review platforms in China. We choose the module of restaurant services for the following two reasons. First, users are relatively more active in this module (Huang et al. 2022). The active user interaction will also generate lots of reviews and corresponding managerial responses. Second, when compared to other service modules, the restaurant module might require relatively higher levels of involvement. That is to say, consumers would spend time checking the existing information such as the managerial responses from the restaurants, trying to make decisions (Gu et al., 2012; Huang et al. 2022).

The descriptive statistics of the key variables show that, on average, the emotion with the highest intensity is anxiety (mean = 0.091; std dev. = 0.106), followed by sadness (mean = 0.048; std dev. = 0.098), disgust (mean = 0.046; std dev. = 0.094), and finally, anger (mean = 0.027; std dev. =0.054). In addition, the average level of customer satisfaction (rating) is 4.615 (std dev. = 0.718), and the average degree of response style matching and content matching is 0.408 (std dev. = 0.155) and 0.646 (std dev. = 0.185), respectively.

In the main model, we adapt multi-visit customers revisiting the same restaurant in less than one year. Model 1 reports the direct effect of MR tailoring on customer satisfaction. Model 2 shows the moderating role of the four basic negative emotions on the influence of MR tailoring. The impact of response style matching on customer satisfaction is more positive with increasing anger (β = 0.607, p < 0. 05), whereas the impact of response content matching on customer satisfaction is less positive with increasing anger (β = -0.114, p < 0. 05). That is to say, for anger-embedded reviews, MRs with higher style matching are more effective than MRs with higher content matching, which supports H1. Similarly, for sadness-embedded reviews, MRs with higher style matching ($\beta = 0.479$, $p < 0.01$) are more effective than MRs with higher content matching ($\beta = 0.013$, $p > 0.10$). H2 is supported.

	(1) Time Window: 360 days		(2) Time Window: 90 days	
	Basic Model	Full Model	Basic Model	Full Model
Rating	0.459***	0.456***	0.437***	0.434***
	(0.011)	(0.011)	(0.029)	(0.030)
StyleMatching	-0.019	-0.015	-0.081	-0.057
	(0.046)	(0.051)	(0.059)	(0.065)
ContentMatching	-0.086	-0.046	-0.093	-0.048
	(0.059)	(0.065)	(0.094)	(0.101)
Anger	-0.059*	-0.066	-0.136***	-0.280
	(0.034)	(0.148)	(0.045)	(0.205)
Sadness	0.005	-0.204*	-0.049	-0.259*
	(0.027)	(0.112)	(0.035)	(0.151)
Anxiety	0.011	0.205	0.033	0.228
	(0.037)	(0.157)	(0.050)	(0.224)
Disgust	-0.024**	0.040	-0.034***	0.099**
	(0.010)	(0.034)	(0.012)	(0.045)
StyleMatching × Anger		0.607**		0.679**
		(0.238)		(0.321)
StyleMatching × Sadness		0.479***		0.467**
		(0.182)		(0.236)
StyleMatching × Anxiety		-0.380		-0.762**
		(0.253)		(0.317)
StyleMatching × Disgust		-0.114**		-0.161**
		(0.056)		(0.076)
ContentMatching × Anger		-0.465**		-0.182
		(0.198)		(0.259)
ContentMatching × Sadness		0.013		0.081
		(0.147)		(0.197)
ContentMatching × Anxiety		-0.053		0.196
		(0.223)		(0.296)
ContentMatching × Disgust		-0.034		-0.103
		(0.048)		(0.063)
IMR	0.684*	0.638*	-0.639*	-0.629*
	(0.376)	(0.377)	(0.352)	(0.353)
Constants	2.321***	2.308***	3.412***	3.338***
	(0.186)	(0.188)	(0.524)	(0.527)
Observations	8413	8413	5013	5013
adj-R^2	0.296	0.298	0.316	0.318

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Control variables are not shown in the table.
Table 1. Moderating Effects of Discrete Negative Emotions on the Impact of MR Tailoring

However, anxiety shows no moderating effect on both response style matching (β = -0.380, p > 0. 10) and response content matching (β = -0.053, p > 0. 10). H3 is not supported. This might be due to the ambiguous threat related to anxiety. Although consumers leaving anxiety-embedded reviews will not deny their ability or chance to cope with the issue, the matched content in MRs might not solve the exact issues the consumer experienced and cope with the ambiguous threat related to anxiety. This would affect the effects of content matching. As for disgust, the impact of response style matching on customer satisfaction is more positive with increasing disgust (β = -0.114, p < 0. 05), whereas the impact of content matching on customer satisfaction is less positive with it (β = -0.034, p > 0. 10). That is to say, for disgust-embedded reviews, MRs with higher content matching are more effective than MRs with higher style matching, which supports H4.

To validate the robustness of our analysis, we conduct several robustness checks. First, we change the time window from one year (i.e., 360 days) to three months (i.e., 90 days). As is shown in table 1, the results are largely consistent with the main model. Second, to alleviate the potential multicollinearity concern from the use of interaction terms, we add the four discrete negative emotions as moderators respectively in the main model. Third, we run the current model with different variable sets in the first step and the current model without using Heckman's (1979) two-step approach. The additional three analyses yield similar results.

Contributions and Future Work

Our research contributes to the current literature in three ways. First, while most studies on MR tailoring point to the importance of MR content (e.g., Huang et al., 2021; Wang & Chaudhry, 2018), our study is among the first to focus on both style matching and content matching in the MR context. By going beyond the content features of MR (i.e., what is said in the MR), we demonstrate that the language style of online reviews (i.e., how the content is conveyed) will play a distinct role when influencing customer satisfaction, providing insights into the effects of MR tailoring strategies. Second, while few studies on MR tailoring have considered the differences among four basic negative emotions expressed in reviews, our research sheds light on the effect of MR for different types of negative reviews. Based on the cognitive appraisal theory of emotion and neuroimaging studies on emotion, we further consider four basic negative emotions (anger, sadness, anxiety, and disgust) expressed in negative reviews and study how these negative emotions affect the effects of MR tailoring. Third, our research studies the impact of MR tailoring on customer satisfaction, considering the emotional expression in negative reviews at the individual level, and thus, adds to the literature on the impact of MR while previous literature on MR to negative reviews using secondary data mainly examined the firm level and rarely analyzed the effect of MR on reviewers (e.g., Huang et al., 2021).

Our findings can provide guidance in practical strategies for managers dealing with negative reviews. Firms should distinguish the MR tailoring strategies in style matching and content matching and pay attention to the discrete emotions expressed in negative reviews. Especially, firms should focus on response tailoring in style for anger-embedded reviews and sadness-embedded reviews and response tailoring in content or anxiety-embedded reviews and disgust-embedded reviews.

While our initial results are promising, the mechanisms are still not explored empirically. Based on the literature on verbal mimicry and communication tailoring, style matching and content matching might mainly affect through providing support for negative emotions appeasing and support for problem coping. And therefore, our future work will conduct in-depth interviews and experiments to further explore and validate these mechanisms. Second, there may still exist endogeneity issues in our model such as other unobserved factors that may confound the influence of the response tailoring. We will conduct more robustness checks for these potential endogeneity issues.

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