7-8-2023

Review Helpfulness as a Function of discrete negative emotions and image colorfulness

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Short Paper

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Abstract

Given that helpful reviews are valuable to both customers and e-commerce platforms, a better understanding of the antecedents for review helpfulness offers clear benefits to review writers and online vendors. This paper proposes two research questions: How will negative discrete emotions expressed through review text (i.e., fear, anger, sadness, and disgust) influence review helpfulness? And how will review textual emotions and image colorfulness of review interactively influence review helpfulness? Using online review of computer related products sold via Amazon in the past five years, we found that anger increase online review helpfulness, while sadness and disgust decrease the helpfulness. We also found the moderating effects of review image colorfulness on the relationship between discrete emotions and online review helpfulness. Our research advances the existing online review literature by proposing the importance of discrete emotions and its interactive effect with review image colorfulness in review helpfulness.

Keywords: Review helpfulness, image colorfulness, discrete emotions

Introduction

Online reviews, particularly helpful online reviews, play an important role in facilitating consumers to make informed decisions and influencing overall sales of e-commerce platforms. Following previous studies (e.g., Yin et al., 2014), we define review helpfulness as the extent to which an online review is perceived by other consumers to facilitate their purchase decisions. A recent report shows that 90% of buyers consider online reviews when making their purchasing decisions (Georgiev, 2021). As such, e-commerce sites attract consumers' attention by identifying and presenting helpful reviews. A typical example is Amazon, which gained an additional $2.7 billion in annual revenues by its online review system and the helpfulness vote mechanism (Spool, 2009). Given that helpful reviews are valuable to both customers and e-commerce platforms, a better understanding of the antecedents for review helpfulness offers clear benefits to review writers and online vendors.

Discrete emotions are expressed by reviewers in their online reviews and perceived by review readers. This research focuses on the connection between discrete emotions and review helpfulness and the moderating role of review image colorfulness. Although extant literature has investigated that emotions can substantially influence helpfulness of online reviews, much of this research has focused on the overall sentiment of the online reviews, omitting the impacts of distinct discrete emotions (Kakaria et al., 2023; Yin et al., 2014), which are defined as distinguishable emotions on the basis of neural, physiological, behavioral and expressive features (Lerner et al., 2015). Drawing on the emotional appraisal theory (Conte et al., 2022; Lazarus, 1991; Lazarus & Folkman, 1984), this research focuses on the effects of key negative discrete emotions on review helpfulness, as negative emotions have stronger impact on review helpfulness than positive ones (Yin et al., 2014). In addition, although existing research pay much attention to review text features characteristics derived from review text (e.g., emotions expressed in review text), the image feature of online reviews is largely ignored. Images enable users to display a broad spectrum of cognition and sentiments in their content (Li & Xie, 2020), and can largely improve consumers' online experience. Drawing on color theory (Agoston, 2013), we propose that colorfulness can influence processing complexity of review and further exert synergistic impacts with discrete emotions on review helpfulness. Specifically, we examine the following research questions (RQs):

> *RQ1: How will negative discrete emotions expressed through review text* (*i.e., fear, anger, sadness, and disgust) influence review helpfulness?*
>
> *RQ2: How will review textual emotions and image colorfulness of review interactively influence review helpfulness?*

This paper proceeds as follows. Section 2 and 3 provide a brief literature review, theoretical basis, and hypotheses development process. Section 4 and 5 describe the method and the preliminary results. We conclude and discuss our contributions and managerial implications in Section 6.

Related literature and theoretical background

Antecedents toward review helpfulness

Sizable research attention has been paid to review helpfulness, largely from review (content) and reviewer (source) perspectives. Previous research has shown that review helpfulness is influenced by review content, such as the length and rating of the review content, and emotions expressed through the content (Choi & Leon, 2020; Srivastava & Kalro, 2019). Additionally, review helpfulness is also influenced by reviewer characteristics such as expertise, identity, rank, and reputation (Xu, 2014). However, although emotions expressed through review content are often examined in online review literature, the positivity of emotions (e.g., valence) is a more important perspective to understand the impacts of emotions (Xu 2014). Besides positivity of emotion, appraisal of emotion also plays a dominant role in decision makings (Lerner et al., 2015), and discrete emotions entails emotional appraisal. Emotional appraisal suggests that discrete emotions result from individuals' cognitive evaluation or response toward environmental stimuli, which can further influence their judgment.

In addition, review images, which are often associated with review text, have also received limited attention. For instance, Amazon.com has listed a separate section to display reviews with images, which suggests the value of review images for review readers. The past few years have also witnessed a major shift from text-centric to visual-oriented experience in online e-commerce platforms (Li & Xie, 2020). In sum, the literature mainly examined the determinants that drive review helpfulness based on users' online review posts, but most of these studies focus on the text content of online reviews (Choi & Leon, 2020; Yin et al., 2014), leaving the role of image content largely unexplored.

Emotional Appraisal Theory

Emotional appraisal theory suggests that discrete emotions are the final products of individuals' appraisal toward the environmental stimuli. Discrete emotions involve several appraisal dimensions beyond valence (i.e., anticipated effort, certainty, attentional activity, and self-other responsibility) (Lerner et al., 2015). Among these appraisals, anticipated effort and certainty are mostly relevant to review helpfulness evaluation, since these appraisals can influence individuals' evaluation of the information accuracy and efforts to gather and present the information (Smith & Ellsworth, 1985). Specifically, Certainty is the degree to which future events seem predictable and comprehensible (high) versus unpredictable and incomprehensible (low). Anticipated effort is the degree to which physical or mental exertion seems to be needed (high) versus not needed (low). Based on these two emotional appraisal dimensions, the four basic negative discrete emotions, including fear, anger, sadness, and disgust (DeSteno et al., 2004), can be further categorized into the following four scenarios.

Firstly, angry emotion has high certainty, since it is associated with confidence about what has happened and about what the cause of the event was (Lerner & Tiedens, 2006). The anticipated effort is also high since the strong arousal and the aggressive feelings associated with anger lead to high cognitive effort (Lerner & Tiedens, 2006). Secondly, fear is associated with low certainty, since fearful individuals are often unsure about what has happened and the exact source of threat. However, fear is associated with high effort, since individuals are vigilant about the situation and spend more cognitive effort to process situational information (Lerner et al., 2015). Disgust also has high certainty, since it originates from human instincts to avoid poisoning or contaminated food, and individuals are often sure what they are disgust toward (Tiedens & Linton, 2001). However, disgust is associated with low effort, since individuals often try to avoid disgusting source and avoid related information processing (Tiedens & Linton, 2001). Lastly, sadness has low certainty, since individuals often feel sad toward situational circumstances that are less controllable and predictable (DeSteno et al., 2004). Sadness is also associated with low effort, since individuals are often depressed and feel reluctant to put efforts (Lerner et al., 2015). The emotional appraisal framework for the four discrete emotions is presented in figure 1.

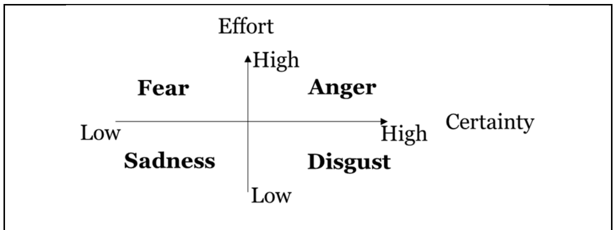


Figure 1. Emotional appraisal framework

Image colorfulness

A notable feature to invoke users' attitude is color (Cyr et al., 2010). Previous studies (Cyr et al., 2010) have shown that color can influence perceived trustworthiness, users' loyalty, and purchase intention. Existing studies mainly examine specific colors (e. g. blue) that influence users' perception toward a user interface. One salient attribute of color is the colorfulness of a picture. For example, an image with more different colors and more equal distribution of these different colors appears more colorful. Colorfulness can evoke both an emotional response of arousal and a cognitive response of complexity (Kim & Kim, 2019), which may interact with the emotional appraisal from the text content of an online review to influence review helpfulness.

Theoretical development

Based on the emotional appraisal theory, and image colorfulness perspective, the following research model is proposed to address our research questions, as shown in figure 2.

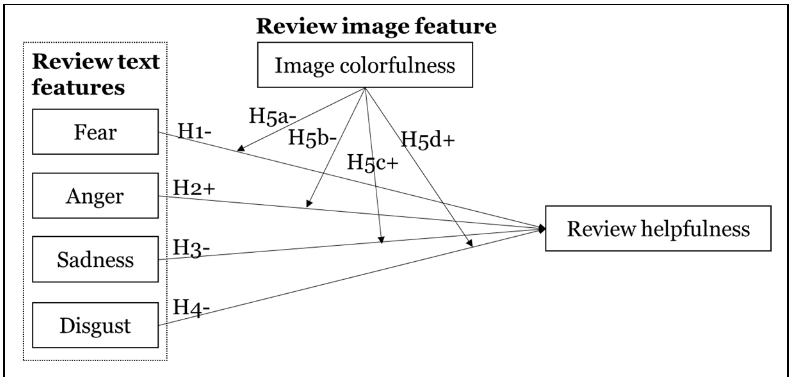


Figure 2. Research Model

Fear involves low certainty and a low sense of control, such that individuals experiencing fear perceive negative events as unpredictable and situationally determined. Certainty is often associated with people's perception regarding the quality of information since it indicates higher information accuracy. Prior study (Schünemann, 2016) suggested that the certainty of a medical diagnostic test has high association with the quality of the diagnostic evidence. Since review readers rely on the review information to make more informed purchasing decision, reviews that convey certain information would be more helpful for readers (Srivastava & Kalro, 2019). Although fear emotion involves a highly anticipated effort for writing the review, it may not offset the negative impact of inaccurate information, associated with certainty.

H1: Fear emotion in review text is negatively related to review helpfulness.

Based on the effort-certainty appraisal of emotions, anger is associated with high certainty and high anticipated effort. In online review context, a high certainty is associated with high accuracy and reliability of information, which facilitates other customers to make more informed decisions. A highly anticipated effort is an indicator of better performance in online review context. More effort from a reviewer in writing the review may indicate that a review is completer and more comprehensive (Yin et al., 2014). Thus, we propose the following hypothesis:

H2: Angry emotion in review text is positively related to review helpfulness.

In contrast to anger, sad emotion is associated with low certainty and low anticipated effort (Lerner et al., 2015). Individuals experiencing sadness perceive negative events as unpredictable and situationally determined. Similarly, in the online review context, sad emotion indicates that the information in the review is less accurate, which is of little value to other consumers. Perceptions that reviews spend limited efforts on the review also lead to an inferior performance of the review. Thus, we expect that sad emotion is linked to a negative perception of the review from other customers in online review context.

H3: Sadness emotion in review text is negatively related to review helpfulness.

Disgust emotion is associated with high certainty and low anticipated effort (Tiedens & Linton, 2001). In the online review context, when consumers perceive the review to be more certain, they often associate accuracy and quality with the review. However, low anticipated effort associated with sad emotion will compromise other consumers' evaluation toward the online review helpfulness. An online review perceived to be written with certainty but with low effort may be considered arbitrary (e.g., the review writer is considered to make this certain argument without a solid basis). Taken together, disgust emotion may negatively influence consumers' evaluations of online review.

H4: Disgust emotion in review text is negatively related to review helpfulness.

Colorfulness is assumed to be strongly related to visual complexity (Li & Xie, 2020). Increasing complexity may increase one's cognitive load for processing image information (Lavie, 2010). Thus, when colorfulness of the image increases, the visual cognitive complexity may compete for other customers' attention for the effort associated with angry and fear (Leahy & Sweller, 2011). This decreased attention toward effort associated with anger and fear will weaken their impact on review helpfulness.

H5a: Image colorfulness negatively moderates relationship between fear emotion and review helpfulness.

H5b: Image colorfulness negatively moderates the relationship between angry emotion and review helpfulness.

When colorfulness of the image increases, we expect that the visual cognitive complexity will not compromise other customers' attention for the effort associated with sadness and disgust. These discrete emotions are already perceived as low effort in writing reviews (Lerner et al., 2015), as explained in figure 1. Cognitive intervention from review image will not further decrease the effort perception. Meanwhile, the image colorfulness may bring more attention to the certainty appraisal of these emotions, since colorful picture entails more details and contrast to the image elements (Kim & Kim, 2019). Thus, the enhancement of certainty appraisal can strengthen the impacts of these discrete emotions on review helpfulness.

H5c: Image colorfulness positively moderates the relationship between sadness emotion and review helpfulness.

H5d: Image colorfulness positively moderates the relationship between disgust emotion and review helpfulness.

The moderating effects of image colorfulness can also be explained by cognitive appraisal theory that the resulting response of a certain event is the consequence of both cognition and emotion (Lazarus,1991).

Methodology

Data source

We collected data by using a self-designed python program. The target is computer related products sold via Amazon in the past five years. Since image features of the reviews are important factors in our study, we only selected reviews with uploaded images in our dataset.

Operationalization of variables

Review helpfulness is measured by the number of helpfulness votes received for a review (Park & Nicolau, 2015; Zhu et al., 2014). To measure discrete negative emotions, we applied the Linguistic Inquiry and Word Count (LIWC) approach (Deng & Chau, 2021; Tausczik & Pennebaker, 2010) to extract words tapping a variety of emotional dimensions and calculate the intensity of discrete emotions based on the number of these specific emotional words. To capture *Colorfulness of review image*, we adopted colorfulness measures in previous studies (Kim & Kim, 2019). We first computed the differences between each color channel of red, green, and blue in each pixel. Their mean and standard deviation across all pixels in a photo were used to calculate the colorfulness of the photo. C is the returned colorfulness matrix.

$$C = \sigma_{rgyb} + 0.3\mu_{rgyb}$$
$$\sigma_{rgyb} = \sqrt{\sigma_{rg}^2 + \sigma_{yb}^2}$$
$$\mu_{rgyb} = \sqrt{\mu_{rg}^2 + \mu_{yb}^2}$$
$$rg = R - B$$
$$yb = \frac{1}{2}(R + G) - B$$

where σ and μ are the standard deviation and the mean value of the pixel cloud.

Control variables: We included control variables, including review score, review quality, review length, and overall sentiment of review, following the selection of control variables in previous online review studies (Yin et al., 2014; Zhu et al., 2014). Firstly, a review score is the score for a product provided by the review writer. The review quality is measured as the overall score reflecting a review's grammar accuracy and collocation accuracy. The review length is measured as the number of words within a review. To measure overall sentiment of a review text, we generated sentiment scores (using Python) by analyzing the online reviews through sentiment analysis and opinion mining algorithms (Lu et al., 2022) using a dictionary of positive- and negative-emotion English sentiment words (Liu, 2010). This dictionary associates a score to each review on the emotions expressed within the words of that text. A larger score indicates less negative sentiment. The final score ranges from -1 to 1, with -1 indicating a strong negative score and 1 indicating a weak or non-negative score.

Data analysis approach

Our dependent variable is a count of the helpfulness vote for the Amazon reviews. Traditional multiple linear regression models would be biased and inconsistent when dependent variable is measured as count variables (Faraj et al., 2015). The dependent variable exhibits overdispersion, as evidenced by the fact that the variance of the dependent variable is substantially larger than its mean. To accommodate for the overdispersion of dependent variable, a negative binomial model is preferred and used in this research.

Preliminary results

Table 1 and Table 2 present descriptive statistics and correlations for the variables used in the analysis. The highest correlation is 0.51, suggesting that these variables are statistically distinguishable. Due to the heterogeneity of measures, all predictors and control variables were standardized before entering the regression model. We applied a stepwise regression approach. The control variables are tested in model 1, followed by the test of main effects in model 2, and moderation effects in model 3. The Log-likelihood value increased from model 1 to model 3, and the AIC decreased from model 1 to model 3, indicating improved model fit in addition to the significant main effects and moderating effects.

Variables	Mean	Std. dev.	Min.	Max.
Review helpfulness	17.32	44.76	2	620
Review score	3.13	1.79	1	5
Sentiment of review text	0.13	0.20	-0.98	1.00
Review quality	13.47	5.85	1.58	117.25
Review length	267.95	317.73	2	3188
Fear	0.05	0.06	0.00	0.33
Angry	0.04	0.05	0.00	0.33
Sadness	0.07	0.08	0.00	0.50
Disgust	0.03	0.04	0.00	0.33
Image colorfulness	37.04	25.97	0.00	174.87

Table 1. Descriptive Statistics (N = 774)

Variables	1	2	3	4	5	6	7	8	9	10
1. Review helpfulness	1									
2. Review score	0.07	1								
3. Sentiment of review text	-0.00	0.51 **	1							
4. Review quality	0.05	0.12 **	0.02	1						
5. Review length	0.25 **	0.15 **	0.04	0.20 **	1					
6. Fear	0.02	-0.17 **	-0.18 **	0.06	0.06	1				
7. Angry	0.05	-0.20 **	-0.32 **	-0.00	0.02	0.30 **	1			
8. Sadness	-0.04	-0.27 **	-0.26 **	0.01	-0.03	0.28 **	0.17 **	1		
9. Disgust	-0.01	-0.23 **	-0.30 **	-0.05	0.00	0.32 **	0.38 **	0.17 **	1	
10. Image colorfulness	-0.03	0.11 **	0.07	0.05	-0.05	-0.09 *	-0.20	-0.09 *	-0.07	1

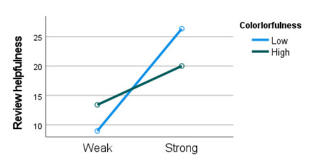
Table 2. Inter-correlations (* p < 0.05; ** p < 0.01)

In model 2 of negative binomial regression (see table 3), the coefficient of fear is non-significant, thus not supporting H1; the coefficient of angry (*β = 0.136, p < 0.01*) is positive and significant, thus supporting H2; the regression coefficients of sadness (*β =- 0.142, p < 0.01*), and disgust (*β = -0.119, p < 0.05*) are both negative and significant, thus supporting H3 and H4. Regarding the moderating effects (model 3), the moderating effect of colourfulness on fear (*β = -0.126, p < 0.05*) and angry (*β = -0.101, p < 0.05*) are both negative and significant, thus supporting H5a and H5b. However, the moderating effect of colourfulness on sadness is non-significant, and thus H5c is not supported. Lastly, the moderating effect of colourfulness on disgust is positive (*β = 0.155, p < 0.01*) and significant, supporting H5d. We further explained the unsupported hypotheses in the discussion section.

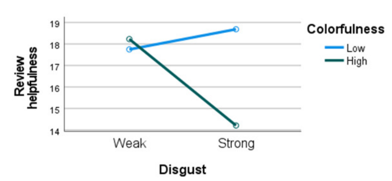
Variables	**Model 1 (Control effect)**	**Model 2 (Main effects)**	**Model 3 (moderating effects)**
Review score	0.118 ** (0.044)	0.079 (0.045)	0.072 (0.046)
Sentiment of review text	-0.103 * (0.040)	-0.109 * (0.044)	-0.108 * (0.044)
Review quality	0.051 (0.055)	0.065 (0.056)	0.081 (0.057)
Review length	0.582 ** (0.046)	0.571 ** (0.047)	0.567 ** (0.047)
Fear (H1)		0.029 (0.045)	0.015 (0.045)
Anger (H2)		0.136 ** (0.047)	0.131 ** (0.047)
Sadness (H3)		-0.142 ** (0.040)	-0.135 ** (0.041)
Disgust (H4)		-0.119 * (0.047)	-0.092 (0.047)
Image colorfulness			-0.019 (0.042)
Fear * Image colorfulness (H5a)			-0.126 * (0.052)
Anger * Image colorfulness (H5b)			-0.101 * (0.046)
Sad * Image colorfulness (H5c)			0.031 (0.042)
Disgust * Image colorfulness (H5d)			0.155 ** (0.048)
Constant	2.676 ** (0.037)	2.659 ** (0.037)	2.647 ** (0.038)
Log-Likelihood	-2,874	-2,862	-2,854
AIC	5,758	5,743	5,737

Table 3. Results of negative binomial regression (* p < 0.05; ** p < 0.01)

a) Interaction between fear and colorfulness



b) Interaction between angry and colorfulness



c) Interaction between disgust and colorfulness

Figure 3. Interaction plots

Discussion and Conclusion

In general, most of our hypotheses are supported, suggesting the important impacts of discrete negative emotions (i.e., fear, anger, sadness, and disgust) in review text on review helpfulness (addressing RQ1) and the moderating impact of image colorfulness (addressing RQ2). The main effect of fear on review helpfulness (H1) is not supported. It is possible that the anticipated effort appraisal has a positive influence while the uncertainty appraisal has a negative influence on review helpfulness. Thus, the two opposing effects offset each other, leading to a non-significant influence. We didn't find a moderating effect of colorfulness on the relationship between sadness and review helpfulness (H5c). The reason might be that sadness has a strong negative influence on review helpfulness through low effort anticipation and low certainty information, and any cognitive attentional split from colorfulness cannot offset this strong negative relationship.

Our research has a strong theoretical contribution to online review literature. Firstly, we show that the textual and image components of online reviews can interactively influence its helpfulness rating. Our research complements the existing online review literature by proposing the importance of discrete emotions. Our research extends the emotional appraisal theory to the online review context and suggests that discrete emotions can also influence online consumers' judgment on review helpfulness. A highly related theoretical lens is the cognitive appraisal theory (Conte et al., 2022; Lazarus, 1991), which classifies discrete emotions along a "certainty appraisal dimension" and a "valence dimension". Our paper emphasizes the importance of the certainty appraisal and its impact on review helpfulness in e-commerce context. Cognitive appraisal theory is also helpful in explaining the moderating role of image colorfulness as colorfulness increases the cognitive complexity which further increases or decreases the effects of negative emotions on review helpfulness. Practically, the results of this study can be used to develop guidelines for creating more helpful online reviews through textual emotion regulation and image colorfulness adjustment. For example, our results imply that online retailers should consider an integrative guideline for writing online review with uploaded images.

There are also several limitations with this study that also lead to future research avenues. Firstly, the research model can be extended to include other antecedents of review helpfulness as control variables. For example, reviewer characteristics have also been shown to influence review helpfulness (Xu, 2014). Secondly, other discrete emotions can be examined, such as positive discrete emotions of happiness, anticipation, etc. Future research can explore other discrete emotions and their impacts on online review. Fourthly, a mix of multiple discrete emotions may occur in online review, and the impact of mixed emotions remains to be explored. There are other features of images, e.g., image clearness that may influence review helpfulness. Lastly, consumers who post images online are often more active than other consumers, and it is possible that our research studies a biased sample who are active online consumers. Future research may examine the impacts of discrete emotions among consumers who are not willing to post images, and examine if the results are still consistent.

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