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RESEARCH ARTICLE

Does Visual Review Content Enhance Review Helpfulness? A Text-Mining Approach

HUAIFENG LI[1] AND JINZHE YAN[2], (Member, IEEE)
[1]School of Information Engineering, Changchun University of Finance and Economics, Changchun 130122, China
[2]College of Business, Gachon University, Seongnam 13120, South Korea

Corresponding author: Jinzhe Yan (yanjz@gachon.ac.kr)

ABSTRACT The previous literature has explored the effects of text review contents and the characteristics of reviewers on the helpfulness of reviews. Moreover, recent research has addressed the role of photos as visual review content, which influences consumers' evaluation of review helpfulness and shapes their decision-making in the consumption of experience goods. From the perspectives of Signaling Theory, Attribution Theory, and Media Richness Theory, this study aims to explore how photos, as visual review content, influence review helpfulness. To test the role of visual content, this study utilized the Yelp Open Dataset and selected restaurants in Florida as research subjects, considering both text and photo content. The LIWC software was used to analyze the sentiment of review contents. The corresponding photos were matched to restaurant codes and then categorized based on food and ambiance. The main findings indicate that positive reviews negatively affect review helpfulness, while negative reviews are positively associated with it. Moreover, the presence of visual review contents (such as photos of food and the environment) moderates the effect of extreme reviews on review helpfulness. Photos attenuate the negative effects of positive reviews and weaken the positive relationship between negative reviews and review helpfulness. By confirming the boundary condition of visual review contents, this study provides new insights that are expected to be useful for future research and offers novel implications for online platforms and business management.

INDEX TERMS Emotion, extreme reviews, media richness theory, photos, review helpfulness.

I. INTRODUCTION

With the rapid evolution of online reviews, user-generated reviews have emerged as a significant source of additional product information and their credibility has significantly reduced consumer uncertainty about unknown products [1], [2]. On one hand, consumers themselves act as creators and contributors to online reviews, sharing their experiences with travel products on review websites and social platforms. However, consumers rely on reviews written by other consumers when making purchase decisions [3]. However, the abundance of individual product reviews, which vary substantially in terms of content, makes it difficult for consumers to identify the key points in reviews and assess true product quality, thus contributing to information overload [4], [5] and hindering their purchase decisions [3], [6]. As a result, among the extensive array of reviews available, consumers tend to give greater consideration to those that prove helpful to them and vote these reviews as "helpful," thus making the helpfulness of reviews a focal point in marketing research [7], [8], [9].

To validate the factors influencing the helpfulness of reviews, scholars have begun conducting explorations from various perspectives, mainly focusing on review contents and reviewer characteristics. Early research in this domain often equated the length of reviews with helpfulness under the assumption that longer reviews are more valuable [10], [11]. Li et al. [12] explore the impact of review text consistency and ratings on review helpfulness from various perspectives. Since then, researchers have gradually introduced the emotional aspects of reviews into their studies, but the results have varied. While some scholars believe that positive reviews are

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helpful, others argue that negative reviews are more valuable [13], [14], [15]. Some studies also suggest that detailed descriptions of nouns, verbs, adjectives, and adverbs positively influence the perceived helpfulness of reviews [16]. Meanwhile, others have explored the readability of reviews, indicating that higher text readability leads to easier comprehension of information, which ultimately positively affects the helpfulness of the reviews [17]. Yi and Oh [18] suggested that the more content about product attributes in a review, the more helpful the votes are, especially for negative reviews.

Another research direction focuses on the sources of review information and how they affect review helpfulness. Representative customers significantly influence their usefulness [19]. For example, factors such as whether a reviewer's real information is disclosed or whether they possess third-party platform certification badges have been considered [20], [21]. Huang et al. [22] suggest that more experienced reviewers can write objective reviews based on their general beliefs. The reviewer's follower count, which reflects the recognition from other platform users, has also been demonstrated to play a role. More followers indicate a reviewer's higher popularity, making their reviews more likely to be approved by consumers [23], [24].

With the upgrading of the built-in functions of smartphones and the widespread use of photography equipment, consumers can express their satisfaction by uploading photos after experiencing products [25]. Online review websites have been enhanced to enable consumers to include photos while posting reviews. Both consumers and platforms embrace the trend of sharing product-related information through photos, thus making it crucial to explore the impact of reviewing photos [26]. With the rapid development of artificial intelligence and deep learning, an increasing number of scholars have begun to focus on how photo reviews affect helpfulness [27].

In research examining review content helpfulness, scholars from various countries have primarily conducted linear causal effect studies, beginning with factors such as review content, reviewers, and product types. In terms of research methods, most studies have relied on traditional linear regression models while using questionnaires or real data from e-commerce platforms for empirical research. Although existing studies have explained the interdependence of online helpfulness and individual explanatory variables, they have only explored linear symmetrical relationships and neglected the combined effects of multiple factors. This prevented the formation of a relatively unified research context and theoretical framework. Inconsistencies have also been observed in research conclusions regarding the impact of explanatory variables on the helpfulness of online reviews. These discrepancies can be attributed to asymmetric causal relationships, which lead to disparate research outcomes. Hence, this study examined textual, photo, and reviewer features to classify them as positive and negative emotions. It also treats photo types as a moderating variable and, based on Signaling Theory, Elaboration Likelihood Model, Attribution Theory, and Media Richness Theory, it explores the following three questions: (1) whether extreme reviews (negative reviews and positive reviews) affect the helpfulness of reviews and if the impact differs; (2) if reviews include photos, whether the impact of extreme reviews on review helpfulness changes; and (3) whether different types of photos, such as photos of food and the environment, moderate the impact of extreme reviews on review helpfulness.

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

A. REVIEW HELPFULNESS

Signaling Theory was originally proposed as a method for studying labor market-related issues, and it suggests that, in markets with asymmetric and imbalanced information, the party with informational advantage can transmit relevant signals about goods to the party with informational disadvantage in different ways, thus reducing information asymmetry in the communication process [28]. With continuous improvements in third-party e-commerce platforms, people have come to prefer post-reviews, and consumers tend to pay attention to product evaluation information before making payments [29]. The definition of online reviews has matured gradually. Park and Lee [30] defined online reviews as positive or negative statements created by consumers regarding products sold online. Mudambi and Schuff [11] described online reviews as expressions of satisfaction or dissatisfaction with products, based on user experiences. Among the numerous variables related to online product reviews, ''review helpfulness'' is most important. As supplements to product descriptions and other information, online reviews have come to play indispensable roles in consumers' purchase decisions due to their credibility [2], accessibility [31], and ability to reduce uncertainty and risk [32], [33].

Mudambi and Schuff [11] defined online review helpfulness as buyers' opinions on corresponding e-commerce platforms, which effectively helps consumers gain deeper insights into product information. Brand type influences review content and has a greater impact on positive reviews than on negative reviews; it decreases over time as more reviews accumulate [18].

To preserve the integrity of online reviews and address concerns regarding their credibility and quality, some online review platforms now offer readers the option of rating reviews. For instance, websites such as Yelp.com and Amazon.com have implemented voting systems in which readers can assess the ''helpfulness'' of a particular review, which eases the burden of information retrieval for consumers [34]. When evaluating review helpfulness, some studies directly count the number of ''helpful'' votes received by reviews [31], [35], while others calculate the percentage of ''helpful'' votes among the total votes [12], [36], [37]. These balancing mechanisms offer a degree of quality assurance and enable readers to quickly identify useful reviews amid thousands of others. Simultaneously, there are studies focused on designing recommendation systems based on the review helpfulness [38], [39].

B. EXTREME EMOTIONAL REVIEWS

The Elaboration Likelihood Model (ELM) is one of the most influential theoretical models in consumer information processing. This model posits that the amount of information can affect individuals' information processing, potentially causing them to depend on peripheral cues in their judgments and decision-making [40]. Attribution theory points out the process of analyzing one's own or others behavior and inferring the reasons for these behaviors. The attribution style influences the strength of subsequent behaviors and motivations [41].

Emotion refers to a unique and transient response to specific stimuli [42] and how one's emotional expression influences the behavior and thoughts of others [43]. Signal theory shows that emotional expressions play a signaling role in expression, as consumers often share their experiential details after consumption, thereby influencing the decisions of other consumers [44]. Recognizing the impact of extreme emotional expressions on review content, many scholars have begun studying subjective factors that affect review helpfulness, such as the language style and content features of reviews [15], [45], [46]. These reviews concluded that extreme emotions can convey direct and distinct signals that are easily understood by unprepared consumers [43]. In various fields, including marketing and e-commerce, numerous studies have begun to employ attribution theory to investigate emotional expressions and their effects on consumer behavior [47], [48].

Among the various possible methods for the sentiment analysis of review texts, the most direct and commonly used approach is based on dictionaries. It involves tokenizing and removing words from review texts, and then calculating the frequency of keywords in the text based on existing sentiment dictionaries or self-constructed ones to determine the sentiment orientation of the text [7]. Some scholars directly use sentiment analysis software to analyze review text [49]. In this method, the input is the review text, and the output is a specific sentiment score indicator. LIWC (Linguistic Inquiry and Word Count) text analysis software is one of the most representative tools for calculating the proportion of words that match predefined dictionaries. The LIWC software has been utilized to analyze review texts and extract word counts related to positive emotions, negative emotions, anxiety, anger, sadness, etc. This approach was employed in a study that examined the influence of rainy weather on consumers' text review behavior [50].

In the restaurant industry, services are intangible and primarily hedonic in nature. The purpose of consumers purchasing these products is not their functionality but rather their intrinsic enjoyment, with consumers buying such products for intrinsic enjoyment rather than mere functionality. Consequently, consumers assess these offerings based on subjective emotional experiences such as pleasure and anger. In this context, extreme emotional information(positive and negative) garners more attention and is more easily processed than cognitive information such as product descriptions [51]. As online reviews represent one of the most authentic forms of advertising, it is important to explore the role of emotional content in restaurant reviews.

C. VISUAL REVIEW CONTENTS (PHOTO REVIEWS)

With the continued development of the Internet and widespread use of smartphones, the number of photos on online platforms has rapidly increased in recent years [52]. According to Media Richness Theory, photos contain rich visual information that is directly conveyed to viewers through sensory perception, thus providing information different from text [53]. For restaurants and similar experiential products, the visual information provided by different types of photos on online platforms is significant to consumers.

Scholars have explored the role of photos on online platforms; however, it is relatively difficult to extract visual information from photos. Early studies in this domain primarily used research methods such as interviews, experiments, and questionnaires and often relied on small-scale data. For instance, Filieri [54] conducted interviews with 38 consumers and found that visual information in online review photos can strongly support the credibility of reviews and help consumers evaluate both the reviews themselves and reviewers. Bigne et al. [55] used eye-tracking and questionnaires to study hotel review ratings, text, and photos, and found that consumers' attention to review photos comes at the cost of reduced attention to text. Beyond experimental and interview-based methods, some scholars have used web scraping to collect photos from online platforms and have conducted empirical studies using econometric models.

Advancements in information technology have expanded the range of the available review formats. In addition to traditional text-based reviews, consumers can submit reviews in the form of photographs and videos. According to the Media Richness Theory, visual content generated by consumers has distinct impacts on understanding conveyed information [56]. Some studies have suggested that photos have a more favorable impact on consumers than text [25]. Creating photo-based reviews requires consumers to consider factors such as color, composition, and aesthetics, making them more time- and effort-intensive than traditional text reviews, and consequently enhancing their credibility. The content of user-uploaded photos and text may also influence how people comprehend the conveyed information [56]. Combining photos and text in reviews can effectively reduce consumers' information uncertainty and boost review helpfulness [3]. Numerous studies have demonstrated that photos are more appealing to consumers than text because they convey more objective information and are generally considered more persuasive [57], [58]. Ma et al. [25] conducted a study using hotel reviews from Yelp and TripAdvisor and found that photos contributed less to review helpfulness than textual content did. However, reviews that integrated both photos and text achieved the highest level of helpfulness.

D. HYPOTHESES DEVELOPMENT

Previous research has demonstrated that the emotions conveyed in online reviews can significantly affect consumers' perceptions of the helpfulness of reviews. Furthermore, emotions that arise during the consumer experience are frequently expressed in user-generated content [45]. These emotions encompass positive, negative, and uncertain medium evaluations, as conveyed by users [13]. Positive and negative reviews are regarded as extreme ratings, signifying product differentiation, and adding diagnostic value to unfamiliar products. Consequently, consumers tend to view extreme reviews as more helpful [59]. Earlier studies also found that consumers are more inclined to write online reviews when experiencing extreme satisfaction or dissatisfaction. This behavior plays a vital role in managing consumers' negative emotions [60].

However, current research findings regarding whether positive or negative reviews are more helpful remain inconclusive. Pan and Zhang [61] suggested that consumers who invest time in perusing reviews tend to have a strong desire to make a purchase and are more inclined to provide positive evaluations, thus creating positive reviews that are more helpful. By contrast, Kim and Gupta [62] discovered that positive reviews do not significantly impact product evaluations. However, Li et al. [63] argued that positive evaluations have a weaker influence on consumer decisions than do negative reviews. This is primarily because an increasing number of consumers have become aware that many positive reviews are fabricated to counteract negative ones, causing potential consumers to perceive these reviews as unreliable [64]. Moreover, positive reviews often lack the level of detail found in negative reviews and may not offer sufficient guidance to potential consumers in their decision-making processes [65]. This is because personal factors often influence positive reviews rather than products or service [66]. Consequently, consumers tend to consider negative reviews more helpful in choosing their products [1], [67] and consider negative emotions more valuable. Negative reviews receive more helpful votes and have a greater influence [68]. As a result, when making decisions, individuals tend to pay more attention to negative reviews than to positive or neutral ones [69]. In summary, this study proposes that online reviews that contain more negative emotional content are perceived as more helpful. Conversely, reviews containing more positive emotional content may not garner as much attention. According to Attribution Theory, consumers are more likely to attribute positive reviews to reviewers themselves. Based on the aforementioned literature, the following hypothesis was formulated:

H1 Positive review contents negatively correlated with online review helpfulness.

H2 Negative review contents positively correlated with online review helpfulness.

According to Media Richness Theory, people interpret information differently when conveyed through user-generated visual content than when conveyed through pure textual content [56]. Visual information in photos has a stronger impact on Internet users' attention and engagement than pure text information [26]. Compared with purely textual descriptions, photos can convey a greater amount of objective information and are more persuasive [58]. Lin et al. [70] observed that reviews containing visual content such as photos and videos were more effective in stimulating consumer interest and increasing purchase intent than reviews containing only text. Ma et al. [25] analyzed hotel reviews on platforms such as TripAdvisor and Yelp, revealing that reviews featuring photos received more helpful votes from consumers than reviews without photos. However, they did not identify the specific types of photos that garnered more helpful votes. The inclusion of photographs in reviews can provide relevant information regarding a product. Cheng and Ho [71] found that online reviews containing more photos and longer text descriptions typically convey more information than reviews containing fewer photos, no photos, and shorter text descriptions. Consequently, online reviews with more photos and longer text descriptions tended to attract more helpful votes.

Do photos in reviews alter consumer perceptions of positive and negative reviews? Attractive food photos often lead consumers to overlook ratings and motivate them to choose a restaurant. However, if consumers give a negative review, they are unlikely to upload positive photos and vice versa. Research has found that consumers are more likely to post reviews with beautiful photos after a positive experience, whereas they may post reviews with unappealing photos if their experience is poor [27]. Suppose a reviewer publishes positive reviews about a restaurant but includes images of a poorly maintained environment. This scenario raises questions about the authenticity of the study, as the information in the text and accompanying images may not align with each other [72]. Consequently, the consistency between textual information and photos can significantly impact the overall credibility of a review [73]. Nazlan et al. [74] examine the influence of photographs on restaurant reviews. They discovered that photos enhanced the helpfulness of positive reviews, although their effect on negative reviews was less pronounced. An et al. [27] also found that consumers are more inclined to post reviews that include photos, which interact with other cues of information such as the sentiment of the review and topics covered in the review. Based on these findings, this study proposes the following hypothesis:

H3: Visual review content (images/photos) moderates the relationship between positive reviews and review helpfulness.

H4: Visual review content (image) moderates the relationship between negative reviews and review helpfulness.

In general, owing to the specific information carried by photos, their impact on the helpfulness of reviews varies.

Yoo [75] explored the effect of including trademarks (brand names) in the visual content on review helpfulness. Xu [76] used text mining to study hotel satisfaction and found that consumers preferred photos with specific information cues related to staff and environment. Giglio et al. [77] studied photos on TripAdvisor and found that the most common photos in reviews depicted interior hotel elements such as rooms and restaurants. Consumers generally consider photos related to hotel interiors to be more helpful than unrelated ones. Oliveira and Casais [78] studied restaurant selection and discovered that consumers prefer photos in reviews, particularly those depicting restaurant spaces and food, rather than promotional photos provided by the restaurant. Yang et al. [79] examined restaurant reviews from the Yelp dataset and identified a positive effect of the number of photos featuring food and beverages on review helpfulness. Consumers tend to hold negative biases when seeing positive and negative reviews, but when they see positive food photos accompanying reviews, their negative bias is mitigated [55]. Other potential consumers may consider mixed reviews (i.e., reviews with accompanying photos) to be more helpful [80], and light pictures to be more attractive than dark ones [81]. An et al. [27] studied the review content of hotels and found that only reviews with photos related to the hotel were considered helpful. They also found that consumers post reviews with photos in both positive reviews of high-star hotels and negative reviews of low-star hotels. The results of the above studies indicate that, when evaluating the helpfulness of photos in online reviews, it is essential to examine which specific information conveyed in the photos is important to consumers.

Consumers may be attracted by textual content and other photos in the review section as they view reviews. Therefore, this study considers all types of photos in the review section and proposes the following hypotheses:

H5: Food photos as visual review content moderates the relationship between positive reviews and review helpfulness.

H6: Food photos as visual review content moderates the relationship between negative reviews and review helpfulness.

H7 Environmental photos, as visual review content, moderate the negative influence of positive reviews on review helpfulness.

H8 Environmental photos as visual review content moderates the relationship between negative reviews and review helpfulness.

Summarizing the proposed hypotheses, we present the research model shown in Figure 1.

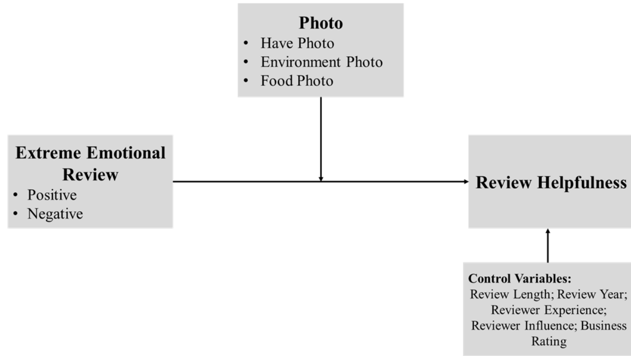

FIGURE 1. Research Model (Created by authors).

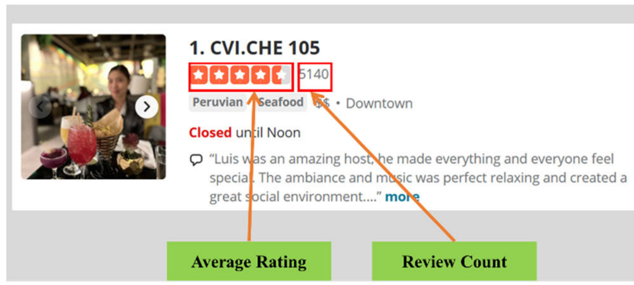

FIGURE 2. An example of a restaurant review summary (Sources: Yelp.com).

III. RESEARCH METHODS

A. DATA COLLECTION

The data for this study are sourced from the Yelp Open Dataset, which includes data on 150,000 businesses in 11 metropolitan areas across the United States. As of this writing, the dataset contains over a million reviews and more than 200,000 photos posted by 700,000 consumers. It encompasses detailed information on businesses, consumers, and reviews, making it a crucial resource for studying online reviews [31], [35], [82].

As Figure 2 shows, consumers can access business ratings, review counts, operating hours, and related reviews on this website.

Similarly, consumers can submit 1-to 5-star ratings, write detailed reviews, and upload photos based on their experience on a website, as shown in Figure 3. Each review included information about the reviewer (number of followers, total review count, and total photo uploads), review details (review date, text, and photos), and helpfulness votes. Therefore, the abundant data resources in this dataset could be used to validate the results of this study.

Based on the research content, all restaurants in Florida were selected as study subjects because Florida is one of the most popular tourist destinations in the United States, with many popular attractions and trending restaurants. People prefer to listen to others' opinions when visiting unfamiliar places. Second, restaurants are experiential products and most prefer restaurants based on consumer reviews. Third, restaurants in this area had the highest number of reviews in the Yelp Dataset. According to the theoretical model of this study, reviews without content, dates, and those not matched to reviewers were excluded. The final dataset included 3,679 restaurants, 75,395 reviews, and tens of thousands of photos of 65,453 consumers.

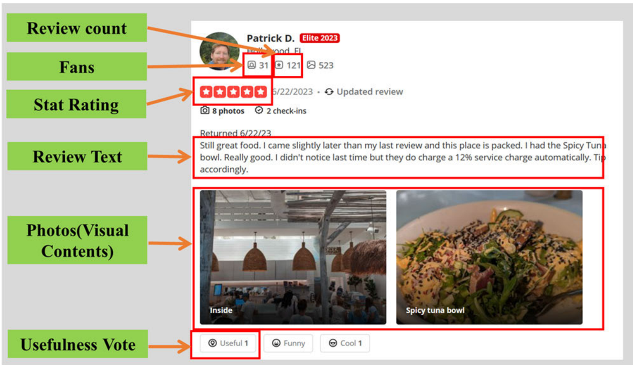

FIGURE 3. Restaurant reviews (Sources: Yelp.com).

B. VARIABLE MEASUREMENTS

1) DEPENDENT VARIABLE

Dependent Variables: The dependent variable is Review Helpfulness, quantified by the total count of "helpful" votes received for the review.

Independent Variables: The independent variables are "Extreme emotional reviews," and the Linguistic Inquiry and Word Count (LIWC) software was used to divide all the reviews into two categories: "Positive Review" and "Negative Review." LIWC is a widely used natural language processing tool that contains a vast number of language categories. It can be utilized to identify emotional expressions in the text, such as sadness, anger, and friendliness, and to calculate the text length. Currently, it is extensively used in marketing and informatic research.

Positive Review is measured by "the ratio of the total number of positive words to the total number of words in a review," following [60] and presented in (1).

$$Positive\ review = \frac{Number\ of\ positive\ words\ in\ review}{Total\ words\ in\ review} \quad (1)$$

Negative Review is measured by "the ratio of the total number of negative words to the total number of words in a review" following [60].

$$Negative\ review = \frac{Number\ of\ negative\ words\ in\ review}{Total\ words\ in\ review} \quad (2)$$

2) MODERATE VARIABLES

The moderation is a dummy variable called "Havephoto," which is used to measure whether a review includes photos (have photo = 1, no photo = 0). Moreover, if the review contained photos, we categorized them into two types: "Envphoto" and "Foodphoto." This study investigates whether different types of photos influence review text helpfulness. Considering that consumers can directly search for all the photos in a restaurant's reviews and then make a comprehensive evaluation, the "Foodphoto" variable is measured by the total number of photos depicting food in the restaurant's reviews. Similarly, the "Envphoto" variable is measured using the total number of photos related to the restaurant's environment, including interior and exterior photos.

3) CONTROL VARIABLES

This study includes five control variables. First, the two control variables were related to the reviewer's experience and influence. Reviewer Experience refers to the total number of reviews the reviewer writes, while Reviewer Influence represents the number of followers the reviewer has. Second, two control variables were related to the review text: Review Length and Review Year. Review Length refers to the total number of words in the review text, whereas Review Year indicates the time difference between the year the review was published and the current year (2023), with a smaller value indicating a more recent review (Equation (3)).

$$Review\ Year = 2023 - Review\ pubulised\ year \quad (3)$$

Finally, a control variable related to business is business rating, which represents the average star rating received by the business, ranging from one to five stars.

Table 1 provides all the variables, their detailed explanations, and reference articles. Table 2 presents the statistical information for each variable.

C. MODEL SPECIFICATION

Given that the dependent variable, review helpfulness, represents a non-negative integer discrete variable, the Poisson and negative binomial regression models are more appropriate for this study than the general linear model. The probability mass function (PMF) for Poisson regression is expressed as:

$$P\,(Y = y) = \frac{e^{-\lambda}\lambda^{y}}{y!} \quad (4)$$

where y represents a random variable that takes integer values, $y = 0, 1, 2 \ldots,$ and $\lambda > 0$. The Poisson model assumes that the mean equals the variance; that is, $Var\,(Y\,|\,X) = E\,(Y\,|\,X) = \lambda$. However, in our dataset, the variance is significantly greater than the mean (Table 2). Therefore, we employ a negative binomial regression model to address and rectify the issue of data overdispersion. The probability mass function (PMF) for the negative binomial is

$$P\,(Y = y) = \frac{\Gamma\left(y + \theta^{-1}\right)}{\Gamma\,(y+1)\,\Gamma\left(\theta^{-1}\right)} \left(\frac{\theta^{-1}}{\theta^{-1} + \lambda}\right)^{\theta^{-1}} \left(\frac{\lambda}{\theta^{-1} + \lambda}\right)^{y} \quad (5)$$

where θ represents the dispersion parameter, λ represents the mean, and the negative binomial model allows variance to be greater than the mean.

Moreover, of the 75,395 reviews, 48,057 (63.74%) received no votes for helpfulness. There could be various reasons for this, such as the fact that the reviews were posted a long time ago, consumers failing to notice the reviews while reading, or a lack of liking and voting. However, this does not necessarily imply that the reviews lack value. Therefore, this study also considered whether a zero-inflated negative binomial regression model could explain the presence of many

TABLE 1. Variable definitions.

Variables	Definitions	References
Dependent variable		
Review Helpfulness	The total number of "helpful" votes for the review	Xu, *et al.* [35] Qazi, *et al.* [83] Guo and Yan [84]
Independent variable		
Positive Review	The ratio of the total number of positive words to the total number of words in a review	Moradi, *et al.* [60] Qin, *et al.* [6]
Negative Review	The ratio of the total number of negative words to the total number of words in a review	
Moderator variables		
Have Photo (Visual review contents)	Dummy variable: 1: The reviews have at least one photo 0: The reviews have no photo	Li, *et al.* [12] An, *et al.* [27] Ma, *et al.* [25] Yang, *et al.* [85]
Environmental Photo	The total number of photos of the environment included in a restaurant review	
Food Photo	The total number of photos of food included in a restaurant review	
Control variables		
Reviewer Experience	The total number of reviews written by each reviewer	Moradi, *et al.* [60]
Reviewer Influence	The number of followers of the reviewer	Li, *et al.* [12]
Review Length	The total number of words in a review	Hong, *et al.* [32]
Review Year	The year 2023 minus the year the review was published	Li, *et al.* [12],
Business Rating	The average star rating of the restaurant	Xu, *et al.* [35], Hong, *et al.* [32]

TABLE 2. Descriptive statistics.

Variable	Obs.	Mean	SD	Min	Max
Dependent variable					
Helpful	75395	0.743	2.046	0	166
Independent variables					
PosReview	75395	6.864	5.440	0	100
NegReview	75395	1.071	1.958	0	37.5
Moderator variables					
Havephoto	75395	0.619	-	0	1
Foodphoto	75395	4.917	10.603	0	71
Envphoto	75395	3.535	7.45	0	43
Control variables					
Experience	75395	446.253	493.04	32	1392
Influence	75395	29.344	44.52	0	155
Length	75395	71.977	58.982	1	1001
Year	75395	6.131	3.561	2	16
Rating	75395	3.825	1.476	1	5

zeros in the dependent variable better. To test the suitability of this model, the Vuong Z-score statistic was examined and found to be less than 1.96, indicating the adoption of the negative binomial regression model. The models were then run with a robust option to report the robust standard errors.

To examine the impact of review text on review helpfulness, this study proposed following model (Equation 6) to test Hypotheses 1 and 2.

$$\begin{aligned} Helpfulness = \alpha_0 + \alpha_1 PosReview + \alpha_2 NegReview \\ + \alpha_3 Exper + \alpha_4 Influence + \alpha_5 Length \\ + \alpha_6 Year + \alpha_7 Rating + \varepsilon \end{aligned} \tag{6}$$

where *Helpfulness* denotes review heedfulness, *Posreivew* represents positive reviews, *NegReview* stands for negative reviews, *Exper* means Reviewer Experience, *Length* denotes review length, *Year* means Review Year, and *Rating* represents the rating of the business. The coefficients α_1 and α_2 represent the effect of the independent variables on the dependent variable, α_3 to α_6 represent the effect of the control variables on the dependent variable, and ε represents idiosyncratic error.

To examine the moderating effect of photo information, this study established model (7):

$$\begin{aligned} Helpfulness = \beta_0 + \beta_1 PosReview + \beta_2 NegReview \\ + \beta_3 HavePhoto + \beta_4 EnvPhoto + \beta_5 FoodPhoto \\ + \beta_6 HavePhoto * PosReview + \beta_7 HavePhoto \\ * NegReview + \beta_8 EnvPhoto * PosReview \\ + \beta_9 EnvPhoto * NegReview + \beta_{10} FoodPhoto \end{aligned}$$

$$* PosReview + \beta_{11} FoodPhoto * NegReview + \gamma C + \varepsilon \quad (7)$$

where *Helpfulness* denotes the review heedfulness, *Posreivew* represents the positive reviews, *NegReview* stands for negative reviews, Hvephoto means the review contains photos along with text review, Envpohot denotes the review including the environment photo of the restaurant, Foodphoto represents the review including the food photo, *Exper* means Reviewer Experience, *Length* denotes the review length, *Year* means Review Year, and the *Rating* represents the rating of the business. *Havephoto*, *Envphoto,* and *Foodphoto*. To measure the moderating effect of visual content, this study generated the interaction term of photos (photos, environmental photos, and food photos) and types of reviews (positive and negative reviews). *HavePhoto*PosReivew, EnvPhoto*PosReivew, FoodPhoto*PosReivew, HavePhoto*NegReivew, EnvPhoto*NegReivew,* and *FoodPhoto*NegReivew* stand for the iteration term of have photo in review and positive review, the iteration term of environment photo included in review and positive review, the iteration term of food photo included in review and positive review, the iteration term of have photo in review and negative review, the iteration term of environment photo included in review and negative review, and the iteration term of food photo included in review and negative review, respectively. Coefficients β_3 to β_8 estimate the effect of the moderating variables on the dependent variable, C represents the control variables, coefficient γ estimates the effect of the control variables on the dependent variable, and ε represents idiosyncratic error.

IV. EMPIRICAL RESULTS

A. EFFECTS OF EXTREME REVIEWS ON REVIEW HELPFULNESS

To examine the impact of emotional features in review texts on review helpfulness (Hypotheses 1 and 2), we conducted regression analysis using Stata for equation (6). Table 3 presents the results.

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As presented in Table 3, the estimated coefficient of PosReview is significantly negative ($\alpha = -0.028, p < 0.01$; column (1)), indicating positive reviews negatively influence review helpfulness, meaning that the more positive a review is, the less helpful consumers perceive it. This result supports hypothesis 1. The coefficient of NegReview is significantly positive ($\alpha = 0.020, p < 0.01$; Column (2)), indicating that negative reviews are positively correlated with review helpfulness. The results showed that the more negative a review is, the more helpful it is perceived by consumers, thus supporting Hypothesis 2. Finally, when we incorporate all explanatory and control variables into the regression analysis, the findings in Column (3) of Table 3 indicate that the coefficients for PosReview and NegReview remain relatively stable, affirming the robustness of the model. Regarding the control variables, Review Length was found to have a significant positive impact on review helpfulness ($\alpha = 0.004, p < 0.01$), suggesting that consumers prefer longer reviews because they consider them to contain more helpful information. Business ratings have a significantly negative impact on review helpfulness ($\alpha = -0.072, p < 0.01$). This phenomenon may occur because in cases where a business maintains a high overall rating, consumers might perceive any negative reviews as isolated incidents, thereby diminishing the perceived helpfulness of such negative review content. Conversely, if a business has a low overall rating, consumers assume that only positive reviews are insufficient to attract them, thus reducing the helpfulness of positive reviews. The coefficient of Review Year is insignificant, and the trend indicates that consumers prefer more recent reviews than older ones do. Neither Reviewer Experience nor Reviewer Influence significantly affects online review helpfulness.

TABLE 3. Effects of extreme reviews on review helpfulness.

	(1)	(2)	(3)
PosReview	-0.028***		-0.027***
	(0.002)		(0.002)
NegReview		0.020***	0.014***
		(0.005)	(0.005)
Experience	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Influence	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Length	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)
Year	-0.003	-0.002	-0.003
	(0.002)	(0.002)	(0.002)
Rating	-0.079***	-0.106***	-0.072***
	(0.007)	(0.008)	(0.008)
Cons	-0.134***	-0.288***	-0.186***
	(0.038)	(0.044)	(0.045)
	0.700***	0.712***	0.700***
_cons	(0.023)	(0.023)	(0.023)
N	75395	75395	75395
Pseudo R^2	0.0178	0.0163	0.0179

B. MODERATING EFFECT OF VISUAL REVIEW CONTENTS (PHOTO)

In alignment with the research model and related hypotheses established in this study, we performed regressions for eqation (7) using Stata 17.0 to explore the moderating effects of photos and different photo types. The results are presented in Table 4.

1) MODERATING EFFECT OF VISUAL REVIEW CONTENTS (PHOTOS)

The moderation of Havephoto (columns (1)– (4) of Table 4) shows that the coefficient of Havephoto∗PosReview is significantly positive ($\beta = 0.022, p < 0.01$), indicating that photos

TABLE 4. Moderating effect of have photo.

Dependent Variable: Review Helpfulness	(1)	(2)	(3)	(4)
	Moderator variable: Havephoto			
PosReview	-0.051***	-0.039***		
	(0.002)	(0.003)		
NegReview			0.052***	0.034***
			(0.004)	(0.008)
Havephoto	-0.476***	-0.562***	-0.530***	-0.409***
	(0.020)	(0.029)	(0.020)	(0.024)
Havephoto* PosReview		0.022***		
		(0.004)		
Havephoto*NegReview				-0.025***
				(0.009)
Foodphoto				
Foodphoto*PosReview				
Foodphoto*NegReview				
Envphoto				
Envphoto* PosReview				
Envphoto*NegReview				
Experience		0.000		0.000
		(0.000)		(0.000)
Influence		-0.000		-0.000
		(0.000)		(0.000)
Length		0.004***		0.004***
		(0.000)		(0.000)
Year		-0.002		-0.002
		(0.002)		(0.002)
Rating		-0.062***		-0.089***
		(0.007)		(0.008)
_cons	0.276***	0.123***	-0.065***	-0.104**
	(0.019)	(0.040)	(0.018)	(0.043)
lnalpha	0.708***	0.655***	0.755***	0.667***
_cons	(0.021)	(0.022)	(0.020)	(0.022)
N	75395	75395	75395	75395
Pseudo R^2	0.0163	0.0237	0.0099	0.0221

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

weaken the negative impact of positive reviews on helpfulness. The results suggest that consumers are less resistant to positive reviews when photos are presented in the review section, highlighting the importance of photos in reviews, and supporting H3. The coefficient of Havephoto∗NegReview is significantly negative ($\beta = -0.025, p < 0.01$), indicating that photos weaken the positive impact of negative reviews on helpfulness, thus supporting Hypothesis 4.

To illustrate the moderating effect of the photos, we computed marginal effects, as shown in Figure 4. Figure 4 shows the helpfulness of the presence or absence of review photographs at different levels of extreme emotional intensity. First, the results demonstrate that the impact of positive reviews on review helpfulness is negative, and that photos play a moderating role. Positive reviews without photos have a stronger negative impact on review helpfulness than those with photos do, indicating that photos weaken the negative impact of positive reviews on review helpfulness. Second, the impact of negative reviews on review helpfulness is positive, and photos play a moderating role in this effect. Negative reviews without photos have a stronger positive impact on review helpfulness than negative reviews with photos do, indicating that photos weaken the positive impact of negative reviews on review helpfulness.

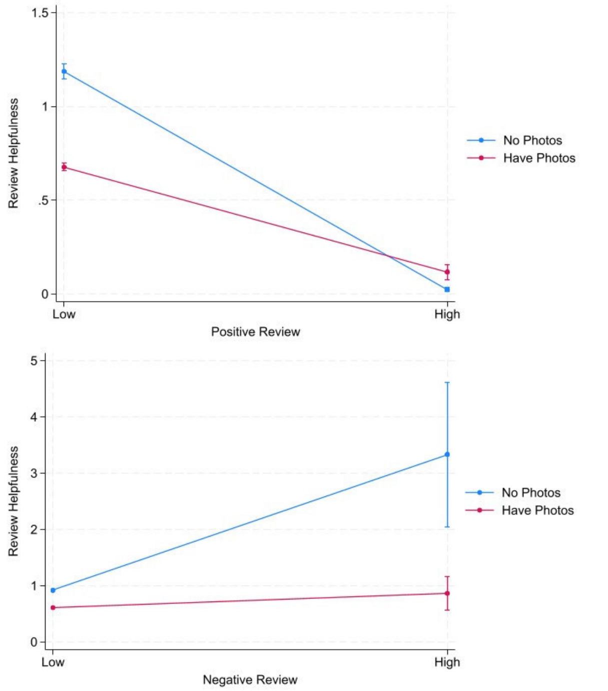

FIGURE 4. The interaction effect of have photos and extreme emotional intensity(Created by authors).

2) MODERATING EFFECT OF VISUAL REVIEW TYPE (FOODPHOTO)

The presence of review photographs moderates the impact of positive and negative reviews on helpfulness. For further analysis, we categorized photos into Foodphoto and Envphoto, and explored the moderating effects of different photo types. First, we study the moderating effect of Foodphoto on the helpfulness of extreme reviews. The estimated moderation effects of the food photos are listed in Columns (5) – (8) of Table 5. The table shows that the coefficient of Foodphoto∗PosReview is significantly positive ($\beta = 0.001, p < 0.01$), which indicates that, as the number of food photos increases, the negative impact of positive reviews on helpfulness improves. This finding supports hypothesis 5. The coefficient of Foodphoto∗NegReview is significantly negative ($\beta = -0.002, p < 0.01$), which indicates that, as the number of food photos in the reviews increases, the positive impact of negative reviews on helpfulness weakens, supporting Hypothesis 6.

Figure 5 illustrates the intensity of the changes in review helpfulness with extreme emotions in reviews with fewer or more food photos. First, the results show that the impact of positive reviews on review helpfulness is negative, and that food photos play a moderating role. Positive reviews with fewer food photos negatively impact review helpfulness compared with positive reviews that contain more food photos. This finding indicates that food photos weaken the negative effects of positive reviews on review helpfulness. In other words, the more food photos included in the reviews, the less likely positive reviews are perceived as unhelpful. Second, the impact of negative reviews on review helpfulness is positive

TABLE 5. Moderating effect of food photo.

Dependent Variable: Review Helpfulness	(5)	(6)	(7)	(8)
	Moderator variable: Foodphoto			
PosReview	-0.062***	-0.033***		
	(0.002)	(0.002)		
NegReview			0.056***	0.028***
			(0.005)	(0.005)
Havephoto				
Havephoto* PosReview				
Havephoto*NegReview				
Foodphoto	-0.009***	-0.014***	-0.010***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Foodphoto*PosReview		0.001***		
		(0.000)		
Foodphoto*NegReview				-0.002***
				(0.001)
Envphoto				
Envphoto* PosReview				
Envphoto*NegReview				
Experience		0.000		0.000
		(0.000)		(0.000)
Influence		-0.000		-0.000
		(0.000)		(0.000)
Length		0.004***		0.004***
		(0.000)		(0.000)
Year		-0.003		-0.002
		(0.002)		(0.002)
Rating		-0.069***		-0.099***
		(0.007)		(0.008)
_cons	0.079***	-0.107***	-0.320***	-0.293***
	(0.016)	(0.038)	(0.013)	(0.044)
lnalpha	0.752***	0.694***	0.806***	0.707***
_cons	(0.022)	(0.023)	(0.021)	(0.023)
N	75395	75395	75395	75395
Pseudo R^2	0.0105	0.0186	0.0027	0.0167

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

and food photos play a moderating role. Negative reviews containing fewer food photos have a more positive impact on review helpfulness than those containing more food photos. This finding suggests that food photos weaken the positive effects of negative reviews on review helpfulness. In other words, negative reviews received fewer votes, as the number of food photos increased.

3) MODERATING EFFECT OF VISUAL REVIEW (ENVPHOTO)

In addition to food-related photos, other types of photos were about the environment, including both the interior and exterior of the restaurant. The estimated moderation effect of the environmental photo is presented in Columns (9) – (12) of Table 6. The coefficient of Envphoto∗PosReview is significantly positive ($\beta = 0.001, p < 0.01$), indicating that, as the number of environmental photos increases, the negative impact of positive reviews on helpfulness improves. Therefore, Hypothesis 7 is supported, which is consistent with the moderating effect of food photos on positive reviews. The coefficient of Envphoto∗NegReview is significantly negative ($\beta = -0.003, p < 0.01$), indicating that, as the number of environmental photos in the reviews increases, the positive impact of negative reviews on helpfulness weakens, supporting Hypothesis 8.

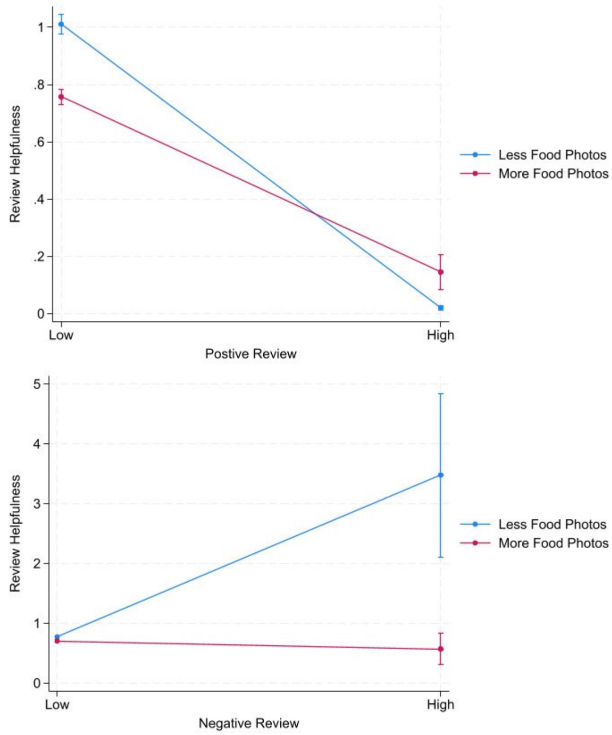

FIGURE 5. The interaction effect of food photos and extreme emotional intensity(Created by authors).

Figure 6 illustrates the intensity of the changes in review helpfulness with extreme emotions in reviews with fewer or more environmental photos. First, the results indicate that the impact of positive reviews on helpfulness is negative and that environmental photos play a moderating role. Positive reviews with fewer environmental photos have a stronger negative impact on helpfulness than reviews with more environmental photos. This finding suggests that environmental photos weaken the negative effect of positive reviews on helpfulness. In other words, as the number of environmental photos in reviews increases, the perceived unhelpfulness of positive reviews decreases. Second, the impact of negative reviews on helpfulness is positive and environmental photos play a moderating role in this effect. Negative reviews with fewer environmental photos have a stronger positive impact on helpfulness than negative reviews with more environmental photos. This finding suggests that environmental photos weaken the positive effects of negative reviews on helpfulness. In other words, as the number of environmental photos in reviews increases, the number of helpful votes for negative reviews decreases.

C. ROBUST ANALYSIS

We adopted the Tobit model and negative binomial regression to test the explanatory power of the selected variables and reliability of the research results. Robustness analysis showed that the coefficients of the main explanatory variables in the Tobit and Negative binomial regression models were

TABLE 6. Moderating effect of environmental photo.

Dependent Variable: Review Helpfulness	(9)	(10)	(11)	(12)
	Moderator variable: Envphoto			
PosReview	-0.057***	-0.032***		
	(0.002)	(0.002)		
NegReview			0.059***	0.027***
			(0.005)	(0.006)
Havephoto				
Havephoto* PosReview				
Havephoto*NegReview				
Foodphoto				
Foodphoto*PosReview				
Foodphoto*NegReview				
Envphoto	0.001	-0.002	-0.001	0.007***
	(0.001)	(0.002)	(0.001)	(0.001)
Envphoto* PosReview		0.001***		
		(0.000)		
Envphoto*NegReview				-0.003***
				(0.001)
Experience		0.000		0.000
		(0.000)		(0.000)
Influence		-0.000		0.000
		(0.000)		(0.000)
Length		0.004***		0.005***
		(0.000)		(0.000)
Year		-0.003		-0.002
		(0.002)		(0.002)
Rating		-0.080***		-0.109***
		(0.008)		(0.008)
_cons	0.047***	-0.125***	-0.364***	-0.304***
	(0.016)	(0.038)	(0.013)	(0.044)
lnalpha	0.758***	0.698***	0.814***	0.710***
_cons	(0.022)	(0.023)	(0.021)	(0.023)
N	75395	75395	75395	75395
Pseudo R^2	0.0096	0.0182	0.0016	0.0166

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

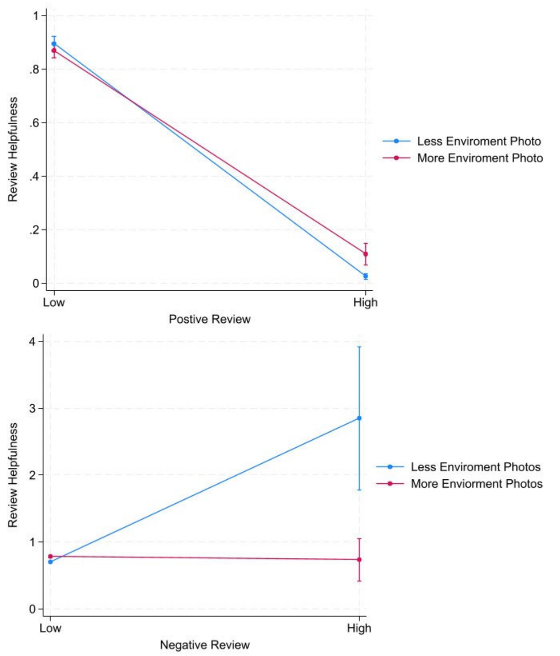

FIGURE 6. The interaction effect of environment photos and extreme emotional intensity(Created by authors).

not significantly different (See Table 7. Moderation effects remained, indicating that the model results were reliable.

TABLE 7. Robustness test results.

	Tobit model		Negative binomial regression model	
	(1)	(2)	(3)	(4)
PosReview	-0.027***	-0.036***	-0.056***	-0.076***
	(0.002)	(0.003)	(0.004)	(0.006)
NegReview	0.014***	0.019**	0.033***	0.041***
	(0.005)	(0.008)	(0.010)	(0.014)
Havephoto		-0.601***		-1.244***
		(0.036)		(0.072)
Havephoto*PosReview		0.017***		0.037***
		(0.004)		(0.008)
Havephoto*NegReview		-0.001		0.000
		(0.010)		(0.020)
Foodphoto		-0.023***		-0.047***
		(0.002)		(0.005)
Foodphoto*PosReview		0.001***		0.001***
		(0.000)		(0.001)
Foodphoto*NegReview		0.000		0.001
		(0.001)		(0.002)
Envphoto		0.040***		0.079***
		(0.003)		(0.007)
Envphoto*PosReview		-0.000		-0.001*
		(0.000)		(0.001)
Envphoto*NegReview		-0.002*		-0.004*
		(0.001)		(0.002)
Experience	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Influence	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Length	0.004***	0.004***	0.009***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)
Year	-0.003	-0.002	-0.004	-0.004
	(0.002)	(0.002)	(0.005)	(0.005)
Rating	-0.072***	-0.064***	-0.154***	-0.142***
	(0.008)	(0.008)	(0.014)	(0.014)
_cons	-0.186***	0.076	-1.528***	-0.850***
	(0.045)	(0.048)	(0.079)	(0.086)
lnalpha	0.700***	0.629***		
_cons	(0.023)	(0.022)		
sigma			4.015***	3.974***
_cons			(0.019)	(0.019)
N	75395	75395	75395	75395
Pseudo R^2	0.0117	0.0167	0.0179	0.0276

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

V. GENERAL DISCUSSION, IMPLICATIONS, AND LIMITATIONS AND FURTHER WORKS

A. GENERAL DISCUSSION

Based on the signal, attribution, and media richness theories, this study proposes a theoretical model of the factors influencing the helpfulness of online reviews and identifies the following knowledge of review helpfulness.

First, consumers tend to find negative reviews more helpful than positive ones, which is consistent with previous studies' results [68], [86]. Extreme negative reviews are perceived to be more diagnostic and persuasive. Negative words indicate a higher degree of product or service flaws, leading to a greater impact on purchase decisions, and in turn, higher helpfulness. According to Attribution Theory, consumers are more likely to attribute positive reviews to the reviewer rather than the product itself or consider them fabricated by the business to counter negative reviews, rendering them less trustworthy. Second, visual review content (photos) moderates the impact of emotional reviews on review helpfulness. According to Media Richness Theory, consumer reviews containing photos are more effective in conveying information than those with pure text, which increases communication efficiency and reduces ambiguity in perception. Photos weaken the negative impact of positive reviews on review helpfulness, indicating that consumers are less resistant to positive reviews when photos are present, underscoring the important role of photos included in reviews. Simultaneously, photos diminish the positive impact of negative reviews on review helpfulness, which differs from our initial hypothesis. This may be because emotional reviews are subjective whereas photos are more objective. In other words, the same photos may convey different messages to different readers, and attractive photos may divert attention from negative reviews [87]. Third, the moderating effects differed depending on photo type. For positive reviews, both food and environmental photos weakened the negative impact on review helpfulness, indicating that photos improve the perception of positive reviews. By contrast, environmental photos reduce the positive impact of negative reviews on review helpfulness, which differs from the moderating effect of food photos. According to Media Richness Theory, visual information cues in photos are easier for most consumers to interpret, which makes it easier to judge whether a restaurant meets consumers' preferences based on environmental photos. However, it is more challenging for consumers to determine whether food is tasting from food photos, which explains why they prefer to search for aesthetically pleasing restaurants while traveling. Fourth, among the other features of review texts, review length has a significantly positive impact on review helpfulness, indicating that consumers prefer longer reviews, thus perceiving them as containing more helpful information. Review timing also indicated a preference for recent reviews. Furthermore, a restaurant's average star rating negatively impacts review helpfulness, meaning that lower-rated reviews have higher perceived helpfulness, which differs from the results of Fang et al. [57]. Regarding reviewer characteristics, reviewer experience and number of followers do not significantly impact review helpfulness, differing from the results of previous studies [24], [88].

B. IMPLICATIONS

1) THEORETICAL IMPLICATIONS

Prior research has mainly focused on objective features (reviewer characteristics), whereas subjective features (review text features) have recently gained attention, particularly in terms of the emotions expressed in reviews [45]. According to Attribution Theory, when inferring reasons for something or the attitudes and behaviors of others, reasons can be attributed to internal or external forces. Therefore, scholars have called for in-depth research to better understand emotions in review texts and potential moderators, including reviewer characteristics (reviewer experience, gender, and information disclosure) [2], [88], along with moderating variables such as product price and type [35]. Based on these considerations, this study reveals how different photo types moderate the influence of review text emotions on review helpfulness, thereby expanding our understanding of the impact of emotional expression on the helpfulness of online reviews.

2) PRACTICAL IMPLICATIONS

These findings have practical implications for online platforms, businesses and consumers. First, businesses should be aware that consumers are more concerned about negative reviews than about positive ones. Therefore, businesses should respond promptly to negative reviews. Second, because including photos weakens the helpfulness of negative reviews, especially environmental photos, businesses should improve their restaurant environments and encourage customers to upload photos after experiencing their services. Finally, as consumers prefer to browse recent reviews, businesses should display reviews with high richness in a clear and prominent area, while also adding appropriate keywords related to product attributes to reduce fatigue in reading reviews and shorten decision-making time, thereby enhancing marketing efficiency.

Compared with text-only reviews, photos and text are more appealing to consumers. The study results indicate that longer reviews are more popular, so consumers can enhance the helpfulness of their reviews by making them more comprehensive and emotionally expressive and having them accompanied by photos that match the text, thus increasing media richness. Disclosing and authenticating personal information on a platform (e.g., showing badges and photos) can increase the reliability of reviews.

Platforms that aim to attract more users and businesses must cultivate a positive online reputation and enhance platform friendliness and authenticity. Reviewers and business information, along with review content and responses, should be carefully reviewed to establish mechanisms that reward reviewers and avoid useless reviews driven by incentives such as gaining points or discount offers. Rewarding experienced reviewers can enhance user engagement, while also guiding less active reviewers to encourage them to write more relevant and helpful reviews for potential consumers.

C. LIMITATIONS AND FUTURE RESEARCH

Although this study constructed and improved a model of the factors influencing the helpfulness of online reviews and derived valuable conclusions, several limitations require further exploration and investigation. First, the review data in this study come from the Yelp dataset and are limited to restaurant reviews in Florida, the USA. Different online platforms and product types may have different configurations for review helpfulness. Future research could compare configurations of online review helpfulness on different platforms. Second, as online reviews increasingly incorporate photos and videos and thus contain more information cues, the present study only introduces text and photos and categorizes photos into food and environmental types while excluding other types of photos. With continued advancements in deep learning algorithms, future research can continue to study the consistency between review text and photos, or even identify video content to explore the impact of unstructured and visualized videos on review helpfulness. Third, this study categorized emotions into positive and negative dimensions. In future research, the considered emotions can be further expanded into dimensions such as anger, sadness, happiness, and joy for more in-depth investigation.

VI. CONCLUSION

This study investigated how photos, as visual review content, influence review helpfulness. The results showd that consumers tend to find negative reviews more helpful than positive ones, consistent with previous studies' results. Moreover, the visual review contents (photo) play a moderating role in the impact of different emotional reviews on review helpfulness. Finally, the moderating effects differ depending on the type of photos. For positive reviews, both food and environmental photos weaken the negative impact on review helpfulness, indicating that photos improve the perception of positive reviews. By contrast, ecological photos reduce the positive impact on review helpfulness for negative reviews, which differs from the moderation effect of food photos.

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HUAIFENG LI was born in 1992. She received the Ph.D. degree in business administration from Gachon University, South Korea. She is currently a Lecturer with the School of Information Engineering, Changchun University of Finance and Economics, Changchun, China. Her research interests include text mining, human–machine interaction, AI-generated content, personalized recommendation services, and marketing strategies.

JINZHE YAN (Member, IEEE) was born in Mudanjiang, China, in 1985. He received the Ph.D. degree in marketing from Sungkyunkwan University, Republic of Korea. Currently, he is an Assistant Professor with the College of Business, Gachon University, Republic of Korea. His research interests include structure modeling, text mining, digital marketing, big data marketing, marketing strategies, personalized recommendation services, and consumer decision-making.