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Information enhancement or hindrance? Unveiling the impacts of user-generated photos in online reviews

Hengyun Li, Lingyan Zhang, Rui (Ami) Guo and Haipeng Ji
School of Hotel and Tourism Management, The Hong Kong Polytechnic University, Hong Kong SAR, China, and
Bruce X.B. Yu
Department of Computing, The Hong Kong Polytechnic University, Hong Kong SAR, China

Abstract

Purpose – This study aims to investigate the promoting effects of the quantity and quality of online review user-generated photos (UGPs) on perceived review usefulness. The research further tests the hindering effect of human facial presence in review photos on review usefulness.

Design/methodology/approach – Based on review samples of restaurants in a tourist destination Las Vegas, this study used an integrated method combining a machine learning algorithm and econometric modeling.

Findings – Results indicate that the number of UGPs depicting a restaurant's food, drink, menu and physical environment has positive impacts on perceived review usefulness. The quality of online review UGPs can also enhance perceived review usefulness, whereas facial presence in these UGPs hinders perceived review usefulness.

Practical implications – Findings suggest that practitioners can implement certain tactics to potentially improve consumers' willingness to share more UGPs and UGPs with higher quality. Review websites could develop image-processing algorithms for identifying and presenting UGPs containing core attributes in prominent positions on the site.

Originality/value – To the best of the authors' knowledge, this study is the first to present a comprehensive analytical framework investigating the enhancing or hindering roles of review photo quantity, photo quality and facial presence in online review UGPs on review usefulness. Using the heuristic-systematic model as a theoretical foundation, this study verifies the additivity effect and attenuation effect of UGPs' visual elements on judgements of online review usefulness. Furthermore, it extends scalable image data analysis by adopting a deep transfer learning algorithm in hospitality and tourism.

Keywords Review photo quantity, Review photo quality, Facial presence, Machine learning, Review usefulness, Heuristic-systematic model

Paper type Research paper

1. Introduction

With the ubiquity of smart devices in today's digitized age, online sharing is an increasingly common way to express one's opinions (Ma *et al.*, 2018). Especially in the

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hospitality and tourism context, online review sites such as Booking, Ctrip and Yelp serve as important platforms for product evaluation. Documenting experiences by taking photographs and sharing them online has become a social phenomenon. The growing popularity of photo sharing has aroused practitioners' and researchers' interest in uncovering the usefulness of user-generated photos (UGPs) and these photos' effects in hospitality and tourism contexts (Ma *et al.*, 2018). As a visual form of user-generated content (UGC), UGPs represent a major source of electronic word-of-mouth (e-WOM) and have been identified as increasingly influential in consumers' decision-making. Photos complement textual reviews and can attract consumers' attention by offering visual cues of travel destinations or service organizations (Li *et al.*, 2021).

Most related literature studied how online review textual content influence review usefulness (Li *et al.*, 2017, 2019), whereas only a limited number of studies have studied the importance of UGPs in e-WOM in hospitality settings (An *et al.*, 2020; Li *et al.*, 2021). Representatively, Yang *et al.* (2017a) found that the number of UGPs showing food and beverages positively affected both perceived usefulness and enjoyment, whereas photos depicting the establishment's physical environment only influenced perceived review enjoyment. However, the study manually coded review photos and only gathered and analyzed data from three restaurants at a certain price level. Their study's generalizability is, thus, limited and may only concern moderately priced restaurants. Analysis based on a larger sample that includes more restaurants, reviews and photos is warranted to assess the external validity. Another aspect of UGPs is quality, which is integral to consumers' evaluations of review photos. To examine the impacts of the "what is beautiful is good" stereotype on consumers' perceptions (Dion *et al.*, 1972), Peng and Jemmott (2018) confirmed that people tend to leave more likes and comments on food photography with higher aesthetic appeal. Different from professional photoshoots, UGPs are generally grainy and imperfect with a low resolution (Marder *et al.*, 2021). Individuals faced with a high volume of reviews may skip over obscure and unclear photos due to the limited information these images convey to save time and effort. However, the role of photo quality on the perceived review usefulness has not been sufficiently examined as an inherent attribute of the visual information in online reviews.

Moreover, photos featuring facial presence and even random faces frequently appear on social networking sites (Fox *et al.*, 2018). Facial presence can mold people's social interactions and judgements, as facial information is usually the first source to emerge during communication. However, images that include facial presence can lead to less attention to the product itself and even information distortion (Guan *et al.*, 2020). From an information processing standpoint, examinations of facial presence as a salient cue are needed to understand UGPs' pervasive power in consumers' perceptions of online reviews – especially for experiential goods in restaurant settings. The role of facial presence in online review photos on users' review feedback behavior (i.e. review usefulness votes) has, thus, remained underexplored.

To fill the abovementioned knowledge gaps, this research draws upon the heuristic-systematic model (HSM) to explore the enhancing or hindering effects of review photo quantity, photo quality, human facial presence in review photos and their interaction on perceived review usefulness. This study contributes to the literature on UGPs in the following ways. First, we innovatively devise a comprehensive analytical framework to explore determinants of UGPs in review usefulness. Second, we apply the HSM to uncover people's complicated systematic and heuristic processing of UGPs by revealing the impacts of noncontent-related cues (i.e. photo quantity and photo quality) and their interaction effects with content-related cues (i.e. facial presence). Third, to the best of the authors' knowledge, this study is one of the first to reveal consumers' perceptions by a machine learning approach and econometric modeling with online big data. Our work facilitates automatic computational analysis of image data – particularly by advancing UGP processing, categorization and analysis in a scalable manner. Managerially, this study enables tourism marketers to capture and use salient features of image-based online reviews.

2. Literature review and hypothesis development

2.1 User-generated photos and online review usefulness: a literature review

Perceived usefulness is a common aspect of information diagnosis and contributes to decision-making (Mudambi and Schuff, 2010). Review usefulness is usually indicated by how many usefulness votes a review receives, representing the sufficiency of reducing product- or service-related uncertainty when consumers have little knowledge about an offering (Liu and Hu, 2021). Research has shown that reviews containing both text and photos are thought to be more helpful (Ma *et al.*, 2018) and have a greater impact on trust creation and purchase intention than reviews containing text or photos alone (Li *et al.*, 2021). Text–photo congruence can generate greater perceived usefulness and indicate higher quality and overall review trustworthiness as well (An *et al.*, 2020).

Previous studies mainly examined the textual components of online reviews, despite the significance of photos. Few studies have extracted quantitative features of photos concurrently, such as the number of photos in a review (Li *et al.*, 2021; Yang *et al.*, 2017b), the inclusion of reviewers' real-profile photos (Park and Nicolau, 2015; Srivastava and Kalro, 2019), the accumulative number of photos in prior reviews (Liang *et al.*, 2020) and review photo content categories (Yang *et al.*, 2017a; Yang *et al.*, 2017b). The relative lack of analytical techniques available for image data (An *et al.*, 2020) have limited the coding and analysis of photos to manual content analysis, which cannot be applied for high-volume data. Some scholars operationalized the presence of review photos as a binary variable (Chung *et al.*, 2017); however, this approach can lead to a potential loss of information implied by the number of photos. We summarize the tourism and hospitality literature on UGPs' impacts on review usefulness and highlights pertinent gaps in Table A1 (see Appendix 1). Different from most studies, our work focuses on review photos and their effects on review usefulness by taking textual attributes as control variables. Our model captures the exact number of photos in a review, quantifies photo quality (as measured by aesthetics and clarity) and detects photo content and facial presence in photos via machine learning algorithms, thereby facilitating automatic and scalable analysis of UGPs. Moreover, we explicate photo characteristics to uncover their independent enhancing/hindering impacts and interdependent interactive effects on consumers' information processing.

2.2 Heuristic-systematic model

This study is grounded on the HSM, which Chaiken (1989) proposed to reveal how information is processed by people. The HSM indicates that people adopt two distinct ways to process information: heuristically and/or systematically. Heuristic information processing enables people to form quick judgements of an object by relying on a few simple information cues (or even only one cue), which is usually noncontent-related. This model assumes that human brain has capacity limits when processing information. That is, people tend to minimize the use of cognitive resources whenever possible (i.e. dominant and unconscious use of heuristic processing; Chaiken and Maheswaran, 1994). Systematic information processing entails careful, thorough and deliberate assessments of issue-relevant cues (Chaiken, 1989), implying a reflective and conscious means of information digestion. This mode requires more time and effort, motivation and cognitive skill. People usually process content-related information cues systematically in an online environment. Heuristic processing and systematic processing are not mutually exclusive but can exert independent (i.e. additivity) or interdependent effects (i.e. attenuation and/or bias effects) on one's judgement when they co-exist (Chaiken and Maheswaran, 1994; Zhang *et al.*, 2014). Examining the persuasive power of UGPs' heuristic and systematic information cues can clarify photos' information-enhancing and hindering effects.

2.3 Hypothesis development

2.3.1 Photo quantity and review usefulness. Photos present information differently than text; in particular, photos possess additional informational value and attention-grabbing ability (Guan *et al.*, 2020). Considering the intuitive understanding of "the more, the better," review photos' quantity may positively affect review usefulness due to several reasons. First, more visuals can simplify information processing and facilitate consumers' decisions (Guan *et al.*, 2020). Drawing on the HSM, the perceived amount of information is a typical heuristic cue that allows for easy judgement and requires little cognitive effort to determine review usefulness. For potential consumers with low expertise who are seeking guidance, reviews that include more photos can convey reviewers' in-depth experience and help reduce the uncertainty of a focal product or service. Second, consumers can construct mental images of products or services using photos (i.e. image-based stimuli; Kim *et al.*, 2014). The presence of more photos in a review provides rich, complementary information and enables viewers to form a detailed consumption vision. This level of depth is especially useful for experiential goods and products. Third, the number of fake or manipulated reviews is increasing (Hlee *et al.*, 2021), and textual reviews can be highly subjective (An *et al.*, 2020). Including more review photos can increase the reliability and authenticity of UGC (Lin *et al.*, 2012), leading potential consumers to find the information more useful. The above discussion inspires the following hypotheses:

H1. Review photo quantity is positively associated with review usefulness.

2.3.2 Photo quality and review usefulness. Individuals' assessments of quality depend on several criteria. Most research in this vein has examined photo quality using visual aesthetic principles that develop rule-based features under photography knowledge (e.g. composition, color and lighting; Li *et al.*, 2010). The notion of aesthetics refers to a process of examining visual elements and then reflecting on them (Zettl, 1999); it is "a concept of artistic value or beauty" (Dickie, 1997), often simply called "beauty" (Jiang *et al.*, 2016). A highly aesthetic image is more likely to convey clear information and lead to effective communication (Guan *et al.*, 2020). Candi *et al.* (2017) have indicated that consumers attend to visual aesthetics, which in turn influence consumers' behavior; consumers generally choose products/brands with positive symbols (e.g. a beautiful appearance) to reflect their self-image (Belk, 1988). Moreover, aesthetic elements are fundamental to consumers' evaluations of product quality (Cyr *et al.*, 2006). Lorenzo-Romero *et al.* (2013) discovered that visual aesthetics could affect consumers' initial impressions of a product within 100 ms. Visual representations help users obtain information as well; when aesthetics is integrated in visual input, people can more easily deconstruct information and develop self-understanding (Zettl, 1999). Pleasing visual aesthetics can, thus, leave a favorable impression (e.g. useful information or design) on a visual presentation in general (Longstreet *et al.*, 2021). According to cognitive load theory focusing on the efficiency of information (Sweller, 2011), negative aesthetic impressions restrict cognitive refinement of information and lower perceived usefulness (Coursaris and Van Osch, 2016).

In addition to photo aesthetics, image clarity can serve as a visual cue of photo quality, which helps users focus on relevant information (Kosara *et al.*, 2002; Kosara *et al.*, 2001). Objects in images with high clarity usually have sharper edges, enabling viewers to easily identify photo content and swiftly judge photo quality. The halo effect relatedly describes a phenomenon wherein a specific, salient characteristic of an object influences one's perceptions of other attributes (Palmer and Peterson, 2016). As photo clarity is a key visual cue when people are initially browsing reviews, it is assumed to color the perceptions of other online review characteristics. On this basis, photo quality, including aesthetics and clarity, is considered a heuristic cue in information processing. The following hypothesis is therefore proposed:

H2. Review photo quality (photo aesthetics and photo clarity) is positively associated with review usefulness.

2.3.3 Facial presence and review usefulness. According to the HSM, content-related information refers to critical systematic cues in information processing (Zhang *et al.*, 2014). Photographs with reviewers' facial presence and even random faces are observable content-related cues on social networks. Some photos are context-based while others are simply selfies that offer limited knowledge about a featured product or service. Guan *et al.* (2020) pointed out that UGPs can include information or distortion that, respectively, facilitates or hinders prospective consumers' purchase intentions. On one hand, review photos with facial disclosure help people become more aware of the other individuals and make online interaction similar to face-to-face communication (Cyr *et al.*, 2009; Guan *et al.*, 2020). Potential consumers, thus, become more involved and compelled to elaborate on such information (i.e. to spend more time reading reviews to glean additional details). Furthermore, photos featuring real faces are less likely to be misinterpreted as fake reviews (Guan *et al.*, 2020). On the other hand, the distortion effect can plague customer-generated photos by misconstruing certain characteristics. For example, when a photo contains irrelevant information (e.g. cues unrelated to the core product), resulting distraction might impede customers' purchase decisions (Yoo *et al.*, 2000). Reviewers' presented identities (i.e. facial presence) can to some extent increase reviews' noticeability and credibility (Cyr *et al.*, 2009); however, a human face can also be a distraction and diminish the quality of provided information (Yoo and Kim, 2012). Li and Xie (2020) confirmed this, and contended that facial presence, such as the selfie of the poster, in social media photos of airline Tweets and sport utility vehicle Tweets may only include personal information, which is not relevant to products, thus, may possibly reducing the subsequent customer social media engagement. Furthermore, random human faces in a photo's background are especially intrusive and may detract from an image's quality and aesthetics while implying a chaotic dining environment (Guan *et al.*, 2020). We, hence, propose the following competing hypotheses:

H3a. Facial presence in review photo(s) is positively associated with review usefulness.

H3b. Facial presence in review photo(s) is negatively associated with review usefulness.

Heuristic and systematic information processing can cooccur simultaneously but one of them can take a prevailing role over the other (Chaiken and Maheswaran, 1994). Researchers have empirically tested these two information processing modes when consumers are presented with different types of information cues (Xiao *et al.*, 2018). Despite that people usually adopt the heuristic information processing first based on the least effort principal, the attenuation effect makes this mode less effective when they are motivated to elaborate on the information more systematically later (Xiao *et al.*, 2018; Zhang *et al.*, 2014). For online reviews, potential consumers are likely to make quick judgements with less cognitive effort first relying on noncontent-related heuristic cues (e.g. photo quantity, photo quality). People typically aim to devote minimal cognitive effort, such as when they do not have enough time to process additional information (Ratneshwar and Chaiken, 1991). Yet the heuristic processing of noncontent-related factors may influence expectations or inferences about content presented in a photo (Zhang *et al.*, 2014) – either positively or negatively (Chaiken, 1989). A review containing many high-quality photos may compel viewers to look more closely at the photo content to acquire useful information. Viewers may then further adjust their perceptions by taking more content-related information into consideration. Thus, facial presence in review photos may weaken initial evaluations based on other noncontent-related cues. Stated formally:

H4a. Facial presence in review photo(s) can weaken the positive effect of review photo quantity on review usefulness.

H4b. Facial presence in review photo(s) can weaken the positive effect of review photo quality on review usefulness.

Figure 1 depicts the framework used in this study.

3. Methodology

3.1 Collection of online review data

Yelp.com is the commonly used restaurant review platform (Li *et al.*, 2019; Park and Nicolau, 2015). To test our research questions and proposed model, we, thus, obtained online reviews [i.e. containing photo(s) only] of 300 restaurants in a famous tourist destination Las Vegas from Yelp in this study. The data set included online reviews posted to Yelp between January 2005 and February 2021. Over the past decade, Las Vegas has received approximately 3,000 awards in areas such as tourism, hospitality, business, entertainment and conservation, cementing its position as one of the top cities in the USA (Davis, 2020). The city's thriving restaurant scene has evolved into a major industry and central attraction.

Based on restaurant attributes (i.e. price level, chain/independent and open/closed), we used a stratified sampling method to select a sample representing all restaurants in Las Vegas. First, based on aforementioned attributes, all Las Vegas restaurants were divided

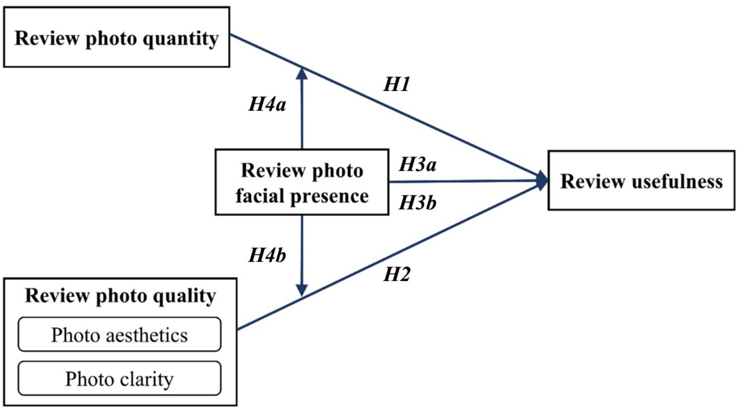

Figure 1.
Research framework

into groups. Then, across groups (e.g. chain restaurants and independent restaurants), we sampled restaurants, respectively, and ensured that the percentage of each category in the sample matched that of the total population in the city. In addition, within each group (e.g. chain restaurants and independent restaurants), restaurants with more reviews had superiority in sampling over those with fewer reviews. Ultimately, our sample of the 300 most reviewed restaurants roughly represented all Las Vegas restaurants. In addition, attributes at the business, review and reviewer levels were considered. A sample restaurant online review with photos is shown in Figure 2. Our formal data set contained 105,237 reviews with 336,092 photos, posted by 61,467 reviewers in total.

3.2 Variable measurement and description

3.2.1 Dependent variables. This study focuses on the effect of characteristics of review photo on the perceived review usefulness. In line with previous work (Li *et al.*, 2019, 2020), the number of review usefulness votes were used as the measurement of customer review feedback, the dependent variable of our study.

3.2.2 Independent and moderating variables. Review photo quantity (*Quantity*). The review photo quantity is measured by the total number of review photos under a review. To better gain the insight of customer online review feedback behavior, in addition to the total number of review photos, we also calculated the number of review photos *by category* for each review. Photos were classified via transfer learning, based on which we identified the number of review photos per category. Pan and Yang (2009) noted that transfer learning can help to solve new tasks based on knowledge in related fields. Specifically, we applied a 34-layer deep residual network (ResNet; He *et al.*, 2016), a model that has been pre-trained in the classical image classification domain, to categorize photos. The official Yelp data set was

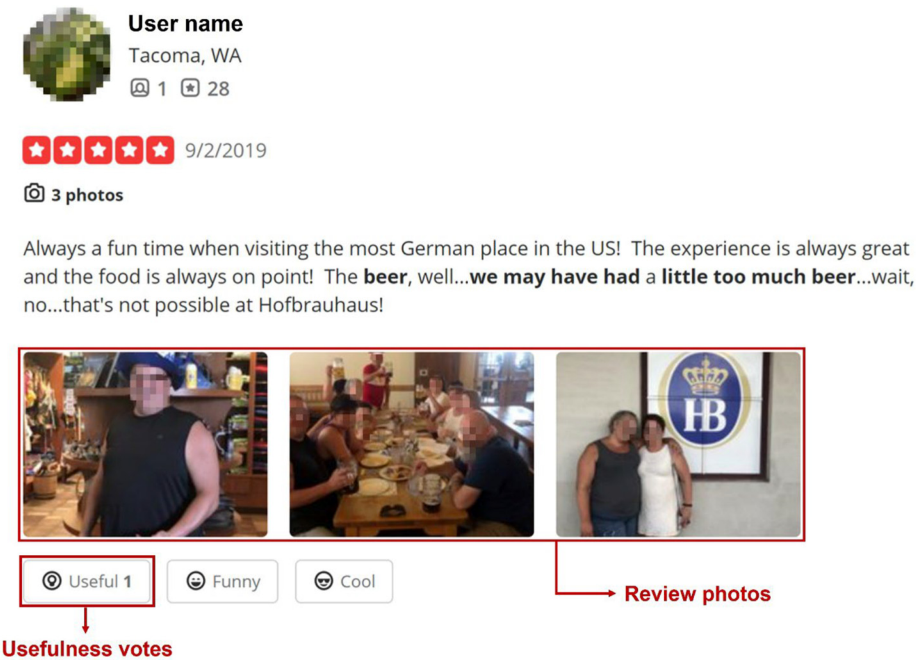

Figure 2.
Sample restaurant online review with photos

used to fine-tune parameters of the model's fully connected layer of the model and all photos were classified into five categories: food, drink, interior environment, exterior environment and menu. A total of 50,000 photos were sampled from official Yelp image data with labels. Then, we randomly chose 90% of these 50,000 images to train the ResNet model; the rest images were reserved for model testing. The distribution of each photo category in the official data set was unbalanced. Therefore, we referred to the accuracy and macro-average to evaluate the model. On average, 96.2% of hold-out sets were classified accurately, and the macro-average was 92.8%. The full photo classification process using transfer learning is depicted in Figure 3.

Review photo quality. We measured review photo quality based on aesthetics and photo clarity (Li *et al.*, 2010; Luo and Tang, 2008). First, we calculated an aesthetic score for each photo in online reviews to measure consumers' perceived image aesthetic quality. The Everypixel Image Tagging API (https://labs.everypixel.com/api/), an image labeling program capable of multiple visual detection tasks (Chen *et al.*, 2021), was used to tag photo aesthetic scores for review photos. This UGC photo aesthetic quality scoring model, which was trained on 347,000 Instagram images, aims to assess the beauty of UGPs in the same manner that a human would. Ten photography experts were invited to evaluate photos' attractiveness, and results were used to train the parameters of a neural network model. Finally, photo aesthetics were indicated by a score ranging from 0 to 1: a higher value reflects a more attractive photo. The review photo aesthetic quality (*Aesthetics*) per review was calculated based on the average aesthetic scores of all photos in a review. Second, review photo clarity was treated as another aspect of review photo quality. Clarity reflects the intensity of three primary color dimensions (i.e. hue, saturation and brightness; Levkowitz and Herman, 1993). Information transmission friction is reduced in photos with high clarity (Zhang *et al.*, 2021). To measure photo clarity, the red–green–blue color space was converted to the hue–saturation–value color space. The percentage of pixels in an image that was clear enough (i.e. with a value between 0.7 and 1) was used to determine the clarity score (Zhang *et al.*, 2021). The average clarity scores of all photos in a review were used to calculate review photo clarity, similar to how photo aesthetics were determined.

Facial presence in review photo (ReviewFace). To identify whether there were faces in a review photo, we used the Faceplusplus API (www.faceplusplus.com/) to estimate the facial presence in review photos. Results showed that 20,589 review photos contained face(s), among which 11,966, 5,188 and 1,748 review photos included one, two and three faces, respectively. These proportions accounted for 91.8% of all photos with face(s). On this basis, we calculated the average number of faces in photos corresponding to a review to measure the variable of facial presence.

3.2.3 Control variables. Studies have demonstrated that the characteristics of reviews and reviewers can significantly influence the review usefulness perceived by customers (Li

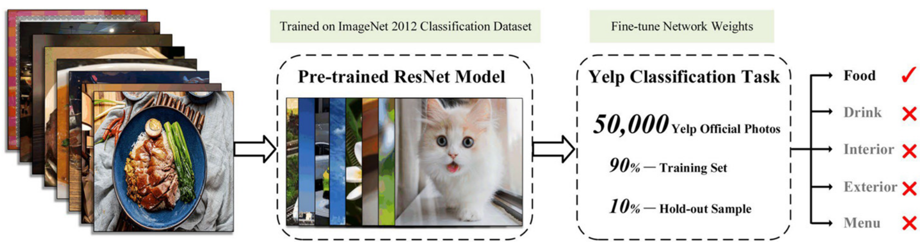

Figure 3. Photo classification process using transfer learning

et al., 2017, 2019; Liang *et al.*, 2019). Therefore, we controlled both review-level and reviewer-level variables to illustrate the effects of photo quantity, photo quality and facial presence in review photo(s). These variables included rating and length of review (i.e. review depth; Leung, 2021), review readability (Gunning, 1969), review exposure duration (i.e. the number of days), a reviewer's expertise (Elite = 1, non-Elite = 0) and the number of Yelp friends and followers. In addition, following a previous practice (Li *et al.*, 2019), we controlled restaurant level-fixed effects to control for the business-related heterogeneity effect.

We show the descriptive statistics of key variables in Table A2 (Appendix 2). The results for bivariate correlation analysis and variation inflation factor (VIF) are also presented (Tables A3 and A4 in Appendix 2). The explanatory variables had relatively weak correlations. The highest VIF in our model estimation was 1.76, which is smaller than 5 and demonstrates no multicollinearity problem (Sheather, 2009).

3.3 Econometric model

As shown in Figure 4, our dependent variable was a count variable that has nonnegative integer values, around half of which were zero. Count data with equal means and variances is required when using Poisson regression (Hausman *et al.*, 1984). Because the variance of the dependent variable was larger than its mean ($\text{Variance}_{Usefulness} = 6.506 > 2.188 = \text{Mean}_{Usefulness}$), a negative binomial regression model (Cameron and Trivedi, 2005) was adopted in this study. The maximum likelihood method was applied to estimate the following specified negative binomial regression models. In addition, we took the logarithm for variables with an absolute skewness value of more than 2 to achieve normality. These skewed variables included *Quantity*, *ReviewFace*, *FoodQ*, *DrinkQ*, *InteriorQ*, *ExteriorQ*, *MenuQ*, *Length*, *Readability*, *Friends* and *Followers*. On this basis, the following models were proposed:

$\mathrm{P}\left(y_{ijk} = n \mid \lambda_{ijk}, \ \delta\right) = \frac{\Gamma(\alpha^{-1}+n)}{\Gamma(\alpha^{-1})\Gamma(\mathrm{n}+1)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\lambda_{ijk}}\right)^{\alpha^{-1}}\left(\frac{\lambda_{ijk}}{\lambda_{ijk}+\alpha^{-1}}\right)^{n}$, where $\alpha = 1/\ \delta$, y_{ijk} denotes review usefulness votes.

$\lambda_{ijk} = \exp(u_{ijk})$, where λ_{ijk} is the mean of review usefulness votes.

On this basis, u_{ijk} was modeled as a function of all aforementioned factors that may influence review usefulness, written as follows:

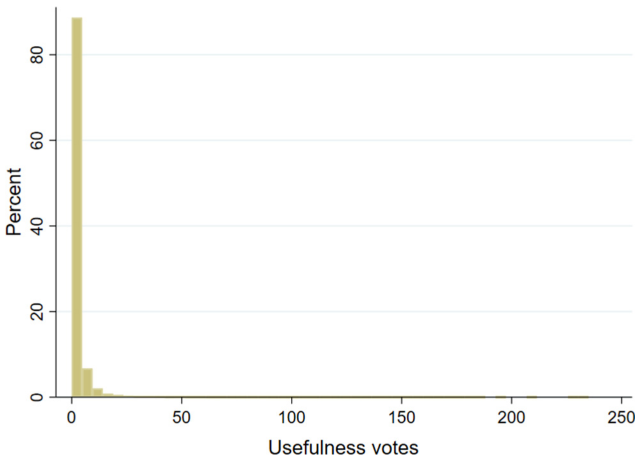

Figure 4.
Distribution of review useful votes

$$
\begin{aligned}
u_{ijk} = {} & \beta_0 + \beta_1 \mathrm{Stars}_{ijk} + \beta_2 \mathrm{logLength}_{ijk} + \beta_3 \mathrm{logReadability}_{ijk} + \beta_4 \mathrm{Date}_{ijk} + \beta_5 \mathrm{Elite}_{ijk} \\
& + \beta_6 \mathrm{logFriends}_j + \beta_7 \mathrm{logFollowers}_j + \beta_8 \mathrm{logQuantity}_{ijk} + \beta_9 \mathrm{Aesthetics}_{ijk} \\
& + \beta_{10} \mathrm{Clairty}_{ijk} + \beta_{11} \mathrm{logReviewFace}_{ijk} + \beta_{12} \mathrm{logQuantity}_{ijk} \times \mathrm{logReviewFace}_{ijk} \\
& + \beta_{13} \mathrm{Aesthetics}_{ijk} \times \mathrm{logReviewFace}_{ijk} + \beta_{14} \mathrm{Clarity}_{ijk} \times \mathrm{logReviewFace}_{ijk} \\
& + \sum_J \lambda_j * R_j + \varepsilon_{ijk}
\end{aligned} \tag{1}
$$

where the subscripts i, j and k, respectively, refer to the indices of the review, reviewer and restaurant; R_j is a dummy variable indicating restaurant fixed effects; and ε_{ijk} represents the standard error.

4. Results

4.1 Main effects of review photo quantity, aesthetics and facial presence

The estimated main effects of review photo quantity, aesthetics and facial presence on perceived review usefulness appear in Table 1. In Model 1.1, we only tested the impacts of control variables on review usefulness. Based on Model 1.1, we added the independent variables *logQuantity*, *Aesthetics*, *Clarity* and *logReviewFace* into Models 1.2, 1.3, 1.4 and 1.5, respectively. Model 1.6 incorporated all four independent variables. The estimation results were consistent across models, and findings regarding the impacts of independent variables aligned with our expectations. Based on the estimation results of Model 1.6, *logQuantity* had a significant and positive relationship with review usefulness ($\beta = 0.171$, $p < 0.01$). In addition, the impact of *Aesthetics* was significantly positive with a coefficient equal to 0.185 ($p < 0.01$); the coefficient of *Clarity* was also positively significant ($\beta = 0.190$, $p < 0.01$). Results further showed that the more visual information and higher-quality photos contained in an online review, the more useful consumers found the review. Therefore, *H1* and *H2* were each supported. Moreover, facial presence significantly and negatively affected ($\beta = -0.065$, $p < 0.01$) review usefulness, conveying lower information reception when review photo(s) contained face(s). As such, *H3b* was supported.

A robustness check was next conducted using subsamples at two price levels. We collected restaurants' price labels on Yelp and divided all restaurants into two groups:

(1) a low-price level, denoted by Yelp price labels of $ and $$ (*Price* = 0); and

(2) a high-price level, denoted by Yelp price labels of $$$ and $$$$ (*Price* = 1).

To examine the model's robustness, we used the independent variables of interest to conduct regression analysis on two subsamples separated by restaurant price level, as shown in the first and second columns of Table A5 in Appendix 3. The estimation results were consistent with the main results in Table 1. In addition, the results shown in the third column tested the moderating effect of restaurant price level to determine whether the magnitudes of coefficients differed significantly between the two groups of restaurants. Stronger effects of review photo quantity and clarity on review usefulness were observed for low-priced restaurants than for high-priced restaurants (coefficient of *logQuantity* × *Price* = −0.111, $p < 0.01$; coefficient of *Clarity* × *Price* = −0.120, $p < 0.05$;), whereas the impacts of *Aesthetics* and *logReviewFace* revealed no significant variation across price levels. These findings accorded with our preceding analysis; our conclusions were, therefore, robust.

4.2 Facial presence in review photo(s) as the moderating variable

The estimated results of models including the moderating effect of facial presence in review photo(s) are listed in Table 2. In Model 2.1, the centralized interactive term *logQuantity* × *logReviewFace* was constructed; in Model 2.2, *Aesthetics* ×

Variable	M 1.1	M 1.2	M 1.3	M 1.4	M 1.5	M1.6
Constant	−3.940***	−3.969***	−3.996***	−4.002***	−3.937***	−4.065***
	(−47.05)	(−47.48)	(−47.17)	(−47.63)	(−47.02)	(−47.97)
Stars	−0.076***	−0.086***	−0.077***	−0.075***	−0.075***	−0.086***
	(−16.55)	(−18.75)	(−16.69)	(−16.44)	(−16.32)	(−18.57)
logLength	0.545***	0.516***	0.544***	0.544***	0.544***	0.513***
	(82.92)	(76.92)	(82.80)	(82.72)	(82.78)	(76.49)
logReadability	0.100***	0.098***	0.100***	0.101***	0.101***	0.099***
	(15.77)	(15.46)	(15.73)	(15.80)	(15.85)	(15.53)
Date	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(−6.06)	(−4.60)	(−5.58)	(−5.71)	(−6.11)	(−3.97)
1.Elite	0.403***	0.395***	0.402***	0.404***	0.401***	0.394***
	(37.29)	(36.56)	(37.21)	(37.39)	(37.09)	(36.45)
logFriends	0.244***	0.240***	0.243***	0.243***	0.244***	0.239***
	(85.90)	(84.57)	(85.71)	(85.67)	(85.93)	(84.24)
logFollowers	0.254***	0.245***	0.255***	0.254***	0.254***	0.246***
	(75.48)	(72.48)	(75.58)	(75.49)	(75.52)	(72.54)
logQuantity		0.169***				0.171***
		(19.98)				(20.19)
Aesthetics			0.279***			0.185***
			(4.34)			(2.84)
Clarity				0.197***		0.190***
				(7.72)		(7.39)
logReviewFace					−0.082***	−0.065***
					(−3.97)	(−3.10)
Business-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
α	0.989	0.980	0.989	0.988	0.989	0.978
LR test of $\alpha = 0$	138,551.107	138,272.504	138,362.884	138,059.037	138,411.928	137,537.481
	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)
LL	−159,411.524	−159,212.524	−159,402.119	−159,381.662	−159,403.663	−159,168.898
LR χ^2	62,015.808	62,413.808	62,034.617	62,075.532	62,031.529	62,501.060
Pseudo R^2	0.163	0.164	0.163	0.163	0.163	0.164

Notes: *Means the coefficient's significance at 10% level; **means the coefficient's significance at 5% level; ***means the coefficient's significance at 1% level; LR: likelihood-ratio; LL: log likelihood

Table 1.
Direct effects of UGPs on review usefulness

logReviewFace was constructed; and in Model 2.3, *Clarity* × *logReviewFace* was constructed. These centralized terms were both introduced into Model 3.4 to investigate the moderating effect of facial presence on the impacts of review photo quantity and review photo quality. Consistent with our above analysis, including more photos and high-quality photos in a review enabled consumers to glean more useful information from the review. The estimation result of Model 2.4 also showed that facial presence in review photos significantly and negatively moderated the effect of the number of review photos on perceived review usefulness ($\beta = -0.086$, $p < 0.05$), validating *H4a*. Furthermore, a negative moderating effect of facial presence was observed between photo quality and review usefulness (coefficient of *Aesthetics*× *logReviewFace* = −0.701, $p < 0.05$; coefficient of *Clarity*× *logReviewFace* = −0.295, $p < 0.05$), supporting *H4b*.

To explain the negative moderating effect of facial presence in review photo(s) more clearly, we calculated the marginal effect at the original value of each observation. Figure 5 depicts how review usefulness correlated with a rise in review photo quantity, indicating the frequency of face(s) in review photos moderated the effects of the number of review photos on review usefulness. Figure 6 displays the relationship of photo aesthetics associated with review

Variable	M 2.1	M 2.2	M 2.3	M 2.4
Constant	−3.967***	−3.982***	−3.996***	−4.056***
	(−47.45)	(−46.95)	(−47.56)	(−47.82)
Stars	−0.085***	−0.076***	−0.075***	−0.086***
	(−18.51)	(−16.45)	(−16.24)	(−18.55)
logLength	0.515***	0.544***	0.543***	0.513***
	(76.73)	(82.68)	(82.63)	(76.45)
logReadability	0.099***	0.101***	0.101***	0.099***
	(15.57)	(15.82)	(15.86)	(15.56)
Date	−0.000***	−0.000***	−0.000***	−0.000***
	(−4.67)	(−5.71)	(−5.77)	(−4.03)
1.Elite	0.393***	0.401***	0.403***	0.393***
	(36.32)	(37.05)	(37.21)	(36.41)
logFriends	0.240***	0.244***	0.243***	0.239***
	(84.62)	(85.77)	(85.72)	(84.28)
logFollowers	0.246***	0.255***	0.254***	0.246***
	(72.56)	(75.61)	(75.53)	(72.54)
logQuantity	0.170***			0.173***
	(20.06)			(20.36)
Aesthetics		0.229***		0.155**
		(3.46)		(2.34)
Clarity			0.182***	0.181***
			(7.05)	(6.97)
logReviewFace	−0.104***	−0.093***	−0.082***	−0.122***
	(−4.92)	(−3.78)	(−3.71)	(−4.78)
logQuantity × logReviewFace	−0.116***			−0.086**
	(−3.01)			(−2.19)
Aesthetics × logReviewFace		−0.564*		−0.701**
		(−1.71)		(−2.08)
Clarity × logReviewFace			−0.264**	−0.295**
			(−1.96)	(−2.19)
Business-fixed effects	Yes	Yes	Yes	Yes
α	0.979	0.988	0.987	0.977
LR test of $\alpha = 0$	137,995.563	138,225.683	137,918.761	137,378.023
	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)
LL	−159,198.952	−159,394.888	−159,374.495	−159,159.928
LR χ^2	62,440.951	62,049.079	62,089.867	62,519.000
Pseudo R^2	0.164	0.163	0.163	0.164

Notes: *Means the coefficient's significance at 10% level; **means the coefficient's significance at 5% level; ***means the coefficient's significance at 1% level; LR: likelihood-ratio; LL: log likelihood

Table 2. Moderating effects of facial presence on review usefulness

usefulness: facial presence shown in review photos moderated the effect of photo aesthetics on perceived review usefulness – that is, the relationship was weakened when review photos contain more frequently faces. In Figure 7, the positive association between photo clarity and perceived review usefulness weakened as the frequency of faces increased. This outcome suggests that a face in review photos reduced the accuracy of information transmission. Faces are common in online review photos. The efficiency of information reception, hence, seems to decline, and information processing becomes more time-consuming.

4.3 Robustness check

4.3.1 Alternative variable of review photo quantity. To further illustrate the effects of photo types on review usefulness, the photo quantity accompanying each review was divided into

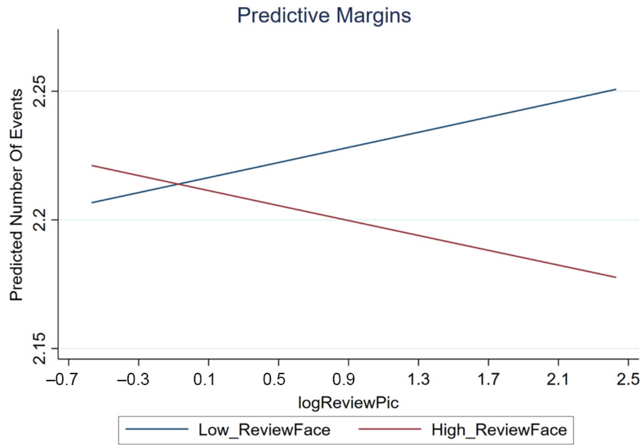

Figure 5. Moderating effects of facial presence on review photo quantity

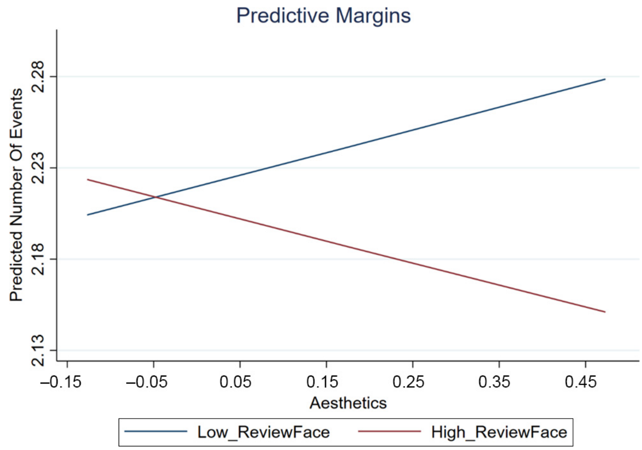

Figure 6. Moderating effects of facial presence on review photo aesthetics

five categories according to Yelp: food photos, drink photos, interior photos, exterior photos and menu photos. Estimation results are attached in Table A6 (Appendix 3). The findings accord with our preceding analysis, meaning our conclusions are robust.

4.3.2 Alternative variable of review photo quality. An alternative measure of photo aesthetics was calculated via a popular recognition service provider, Baidu (https://cloud.baidu.com/), which enabled us to analyze image noise, blur, occlusion and so on. Moreover, we determined the clarity of review photos using Tenengrad Criteria (Pech-Pacheco *et al.*, 2000), a gradient-based approach that has been frequently used to quantify image sharpness (or clarity). The new models were re-estimated after review photo quality variables were re-entered (Table A7 in Appendix 3). The findings were consistent with those shown above.

4.3.3 Controlling additional review factors. We considered other variables that may influence customers' perceived review usefulness but were not explicitly specified at first. We added review breadth and review sentiment as control variables, which have been related to review usefulness in prior studies (Leung, 2021; Siering *et al.*, 2018). Review

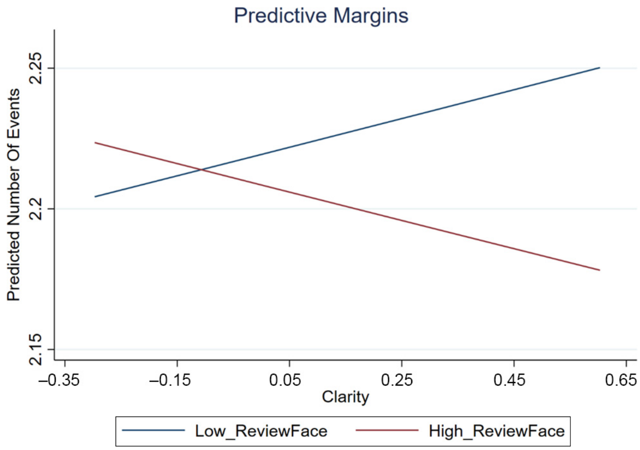

Figure 7.
Moderating effects of facial presence on review photo clarity

breadth was measured based on the number of product attributes that consumers mentioned in online reviews (Leung, 2021). The topics/aspects covered by review text were extracted using a latent Dirichlet allocation model, which processes review text corpus as input and outputs topic keywords and document (i.e. review text) topic vectors. Based on confusion and consistency indices, we extracted five topics from the model and calculated the number of topics in each review as the review breadth (Zhang *et al.*, 2019). To assess review sentiment, we used a sentiment model named Valence Aware Dictionary for sEntiment Reasoner (VADER) via a natural language toolkit package in Python (Hutto and Gilbert, 2014; Loper and Bird, 2002). VADER can identify the sentiment of textual content on social media in line with certain rules and lexicons. After adding these variables in the model, we reestimated the models and obtained results consistent with our initial findings. Our conclusions were accordingly robust (Table A8 in Appendix 3).

4.3.4 Controlling unobserved temporal heterogeneity. We used a set of time dummy variables as control variables to reflect time-varying voting patterns in different months and years to avoid spurious regression. These controls were used to absorb any variation that may occur systematically in peer assessment votes due to time-specific exogenous variables. The newly estimated results (Table A9 in Appendix 3) echoed our preceding analysis, further confirming the findings' robustness.

5. Conclusion and implications

5.1 Findings and discussion

This study explored how heuristic and systematic information cues in UGPs can influence potential consumers' perceived usefulness of peer-written reviews. Using econometric methods and machine learning algorithms in image data analysis, this study investigated the effects of online review photo quantity, quality and content on perceived review usefulness. Photo quantity and photo quality were found to be significant heuristic cues when potential consumers were evaluating online review usefulness. By contrast, facial presence functioned as an important systematic cue and expedited a significant but adverse process of usefulness evaluation. Our main findings are as follows.

First, consistent with results from Yang *et al.* (2017a) in the restaurant setting and An *et al.* (2020) and Li *et al.* (2021) in hotel contexts, this study further validates that online review UGP quantity positively influences the perceived review usefulness. We argue that this positive effect is the result of human's heuristic information processing; more quantity of photos is inferred as more informative, which is a conclusion that requires little cognitive efforts for potential consumers to make. Moreover, people who are browsing reviews for advice generally have limited knowledge about the product to be chosen, and they often have access to a large number of alternative reviews for reference. Reviews containing more photos may be more attention-catching and have a greater chance of being read.

Second, our findings show that online reviews with high-quality UGPs can boost perceived review usefulness. Aesthetics can awaken brain areas associated with emotion (Muñoz-Leiva and Gómez-Carmona, 2019) and clarity can help people identify and focus on the relevant information (Kosara *et al.*, 2002). High-quality product images often evoke positive emotions in consumers, making it easier to evaluate information positively. Drawing on the HSM, the enhancement effect of photo quality (as measured by aesthetics and clarity) is a salient heuristic cue that influences perceived review usefulness and may determine whether people linger over a review. In addition, various contextual factors may interplay behind the enhancement effect. For instance, individual attitudes and behaviors are more susceptible to visual aesthetics in a "low information rationality" environment (e.g. online markets).

Third, unlike prior studies reflecting the positive impacts of human faces in UGPs on product evaluation (Guan *et al.*, 2020) and brand image (Nanne *et al.*, 2020), this study demonstrates the negative effect of facial presence in UGPs on review usefulness. When more faces are captured in photos, customers perceive a review as less useful. A possible explanation is that a photo's perceived information on quantity and quality can be reduced when more faces are shown in photos, possibly leading consumers to express negative perceptions of the provided images and information (Jiang *et al.*, 2016). Moreover, human faces are unrelated to core products in the hospitality context; therefore, an increasing number of faces can distract consumers' attention and even imply a chaotic dining environment (Guan *et al.*, 2020; Yoo *et al.*, 2000). An irrelevant facial presence may diminish people's expectations and weaken their initial perceptions. We further tested the moderating effects of facial presence and found that facial presence in review photos could detract from the positive impacts of review photo quantity and photo quality on review usefulness. Supported by the HSM, content-related cues (i.e. facial presence) and noncontent-related cues (i.e. photo quantity and quality) can jointly shape one's judgement (Xiao *et al.*, 2018).

5.2 Theoretical implications

This paper makes several contributions to the UGPs and online review usefulness literature in the hospitality. First, our work presents an innovative and comprehensive analytical framework for assessing UGPs' effects on review usefulness by considering review photo quantity, photo quality and photo content assessed via the HSM. In responding to calls to investigate visual UGC in greater depth (Li *et al.*, 2021), our study considered review photos. Although several existing studies (Li *et al.*, 2021; Yang *et al.*, 2017a) have examined the effect of review photo quantity and content, this study further examines the relation between another important attribute of online review UGPs, i.e. photo quality, and the review usefulness, which constitutes a more comprehensive understanding of UGPs in online reviews. By drawing on the HSM, this study verifies the additivity effect of heuristic cues (i.e. photo quantity and quality) and systematic cues (i.e. facial presence) in UGPs on review usefulness. We have also revealed the attenuation effect of systematic cues on heuristic cues when both cues apply to consumers' information processing (Chaiken, 1989; Xiao *et al.*, 2018; Zhang *et al.*, 2014).

Second, as to various social media cues that attract attention from the viewers (Simonetti and Bigne, 2022), this study is one of the first to examine the effect of facial presence on consumers' perceptions of review usefulness. Most UGC-related research has investigated the disclosure of real photos as reviewers' avatars (i.e. profile photos) alongside reviews (Park and Nicolau, 2015). Our study instead focused on facial presence in review photos. Extending this line of work around facial disclosure in UGPs (Guan *et al.*, 2020; Nanne *et al.*, 2020), we formulated competing hypotheses and identified an adverse effect of facial presence on consumers' perceptions of reviews. The complex impacts of UGPs, thus, depend on content. Guan *et al.* (2020) contended that UGPs could have both information and distortion effects. Our study advances the literature on specific UGP characteristics resulting in the distortion effect.

Third, this study extends scalable image data analysis by adopting a deep transfer learning algorithm in hospitality and tourism. In a pioneering study, Yang *et al.* (2017a) manually coded review photo data. A limited body of recent research (An *et al.*, 2020; Li *et al.*, 2021) has since incorporated deep learning to analyze scalable review photo data in a hospitality context. This study enhances UGP analysis by integrating a deep transfer learning algorithm with econometrics to explore the relationship between photo content and consumers' perceived review usefulness, which went a step further in addition to extracting hidden patterns from big data (Lee *et al.*, 2021).

5.3 Practical implications

To conduct effective online and social media marketing, online review platforms and business owners must recognize the significance of UGPs as an important source of e-WOM. The findings of this study provide several practical industry insights.

First, for restaurants, managers should encourage customers to post more photos displaying core products, such as food for restaurants. Most importantly, aside from increasing attention to UGPs' quantity and content, managers should also ensure the quality of basic attributes first (e.g. food hygiene and the dining environment) to fundamentally improve UGP quantity and quality.

Second, UGP is a double-edged sword. The content, composition, design, aesthetics and overall quality of photos can facilitate or hinder information presentation and positively or negatively affect one's perceptions (Guan *et al.*, 2020). Practitioners can implement tactics to potentially improve UGP quality. On the one hand, restaurants can train their employees or hire a professional photographer to help customers take aesthetically appealing photos. On the other hand, restaurants should be aware of the negative impacts of UGPs containing many human faces and other elements that may reduce the perceived luxury, uniqueness and hedonic value of high-end restaurants.

Third, our findings can serve as a reference for online review sites to develop professional algorithms for image-processing that are able to identify reviews with useful and pleasing UGPs (Li *et al.*, 2021), such as those presenting core attributes and relevant content, and place them in prominent positions on the site. Platforms can incorporate image-filtering tools to enable UGPs to be better crafted and more presentable. Furthermore, they should also consider designing an incentive mechanism to encourage consumers to post reviews containing high-quality photos, thus, prompting greater review usefulness.

5.4 Limitations and future research

The current study is not free from limitations that offer directions for future work. First, the effects of other UGP attributes (e.g. photo sentiment) on perceived review usefulness were not tested in this study. In addition, we only controlled the most common variables in our regression models due to model efficiency. Future research can investigate the effects of other UGP dimensions on consumers' perceptions and further control other relevant variables. Second, the effects of UGPs on other meaningful outcomes, such as consumer engagement, product ratings, brand loyalty and financial performance, were not considered. Third, due to technical constraints, we could not identify whether the facial presence in UGPs was the reviewer (i.e. a selfie) or other people (e.g. service staff, dining companions or other customers). Future studies can divide facial presence into different types to evaluate distinct effects and explore why faces in photos make a review less useful. Analysis of facial presence (e.g. emotions, expressions, personal demographics and physical attractiveness) may indicate which types of facial presence are likely to be seen as less useful. Fourth, due to the data availability, this study only focuses exclusively on restaurant data in Las Vegas. Such a city-based study provides limited insights as to the possible regional heterogeneity. Subsequent work can incorporate data from multiple cities to further verify the research findings from our study. Last, the role of photo anonymity on review usefulness should be investigated. Empirical evidence suggests that anonymity influences reviewers by providing opportunities to leave negative reviews under the veil of anonymity (Deng *et al.*, 2021). Photo anonymity should, hence, be considered as another noncontent-related cue in review usefulness.

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Appendix 1. Literature review

Table A1. Research on UGPs' effects on review usefulness in tourism and hospitality

Study	Image factors	Other factors	Outcomes	Image data coding
Racherla and Friske (2012)	Reviewer profile photo disclosure	Review exposure duration; reviewer expertise; reviewer reputation; review rating; review extensiveness; SEC classification of goods and services	Review usefulness	Presence of reviewers' profile photo taken as binary variable (0,1)
Park and Nicolau (2015)	Reviewer profile photo disclosure	Reviewer expertise; reviewer reputation; review elaborateness; review readability; reviewer name disclosure; review rating	Review usefulness; review enjoyment	Presence of reviewers' profile photo taken as binary variable (0,1)
Chung *et al.* (2017)	Reviewer profile photo disclosure; review includes hotel photo(s)	Reviewer profile name disclosure; reviewer expertise; review rating; review length; cognitive level of review; degree of negativity	Review usefulness	Presence of reviewer profile photo and review photo(s) taken as binary variable (0,1)
Yang *et al.* (2017a)	Number of physical environment images; number of food and beverage images	Review length; review readability; number of reviews; number of friends; elite badges; star rating	Review usefulness; review enjoyment	Manually coding photo content category
Yang *et al.* (2017b)	Review photo category	Review length; reviewer location; reviewer level; reviewer helpfulness votes; review rating	Comparative importance of review characteristics on review usefulness	Manually classifying reviews of a case study hotel by attaching no photos, attaching hotel-related photos, attaching unattractive hotel-related photos and taking the category with the maximum value to label the review
Djafarova and Deluce (2018)	Review includes hotel photo(s); review photo quality; review photo category; photo source	Review rating	Review usefulness	Manually classifying review photos by content categories and by photos' quality (i.e. low, medium and high); taking the average of review helpfulness for predefined sets of photos and testing statistical differences

(*continued*)

Study	Image factors	Other factors	Outcomes	Image data coding
				among sets (i.e. reviews with vs. without photos, management vs. UGPs, photos of different quality and photo categories)
Ma *et al.* (2018)	Holistic image features (specific features were not extracted)	Text content features	Predicted review usefulness	Using deep residual network to represent image features
Srivastava and Kalro (2019)	Review image count; reviewers' profile photo disclosure	Reviewers' profile disclosure; reviewer reputation; reviewer expertise; number of reviews/ contributions; review rating; review length; review comprehensiveness; review clarity; review readability; review content relevancy; review valence	Review usefulness	Manually extracting and coding all latent information from image data
An *et al.* (2020)	Review photo content; Photo–text congruence	Hotel class; review length; review readability; review text content; review sentiment	Review usefulness	Using a supervised machine learning algorithm to classify photos into five categories based on classification from TripAdvisor and domain experts; using pretrained neural captioning model to generate image captions and match with vectorized review text by TF-IDF
Li *et al.* (2021)	Number of room-related objects in photos; number of food and beverages-related objects in photos; presence of UGP in a review	Hotel price; review valence; number of followers; hotel management response	Review usefulness	Using deep learning to identify guest room-related and food and beverages-related objects shown in review photos; presence of review photos taken as binary variable (0,1)

(continued)

Table A1.

Study	Image factors	Other factors	Outcomes	Image data coding
Our study	Photo quantity (five categories: *Food, Drink, Interior, Exterior, Menu*); photo quality (measured by *Aesthetics* and *Clarity*); Facial presence in review photos	Review length (i.e. review depth); review breadth; review readability; review rating; review sentiment; review exposure duration; reviewer expertise; number of friends and followers; month- and year-fixed effects; Business-fixed effects	Review usefulness	Counting the exact number of photos in a review as photo quantity; using transfer learning to categorize photo content under five categories and taking the number of each photo category in a review as an alternative variable for photo quantity; applying machine learning algorithms to calculate review photo quality, measured by photo aesthetics and photo clarity; applying machine learning to automatically detect the amount of facial presence in review photos

Notes: SEC = search, experience and credence-based; TF-IDF = term frequency-inverse document frequency

Table A1.

Appendix 2. Descriptive statistics, correlation and collinearity analysis

Variable	Obs.	Mean	Std. Dev.	Skewness	Min	Max
Usefulness	105,237	2.188	6.506	11.336	0	235
Quantity	105,237	3.194	2.870	3.067	1	50
FoodQ	105,237	2.317	2.282	3.026	0	49
DrinkQ	105,237	0.179	0.490	5.646	0	27
InteriorQ	105,237	0.441	1.013	4.187	0	28
ExteriorQ	105,237	0.113	0.408	5.144	0	9
MenuQ	105,237	0.143	0.557	6.581	0	14
Aesthetics	105,237	0.246	0.074	0.897	0.119	0.890
Clarity	105,237	0.297	0.177	0.667	0	0.988
ReviewFace	105,237	0.129	0.533	9.316	0	19

Table A2. Descriptive statistics of key variables

Table A3.
Correlation analysis of explanation variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. logQuantity	1.000																
2. logFoodQ	0.799	1.000															
3. logDrinkQ	0.287	0.053	1.000														
4. logInteriorQ	0.425	−0.017	0.078	1.000													
5. logExteriorQ	0.237	−0.025	0.041	0.194	1.000												
6. logMenuQ	0.299	0.036	0.075	0.145	0.107	1.000											
7. Aesthetics	0.053	0.216	0.008	−0.167	−0.058	−0.176	1.000										
8. Clarity	0.013	0.100	−0.042	−0.144	−0.054	0.070	0.148	1.000									
9. logReviewFace	−0.018	−0.203	−0.010	0.319	0.064	−0.015	−0.140	−0.096	1.000								
10. Price	0.190	0.157	0.031	0.109	0.039	−0.029	−0.022	−0.015	0.009	1.000							
11. Stars	0.050	0.053	0.048	0.011	0.009	−0.036	0.051	−0.028	0.050	0.017	1.000						
12. logLength	0.321	0.278	0.096	0.105	0.070	0.112	0.016	0.038	−0.059	0.117	−0.192	1.000					
13. logReadability	0.162	0.123	0.041	0.091	0.061	0.051	−0.010	0.004	−0.011	0.092	−0.082	0.383	1.000				
14. Date	−0.021	−0.004	−0.013	−0.014	−0.014	−0.057	−0.128	0.010	−0.033	0.046	−0.082	0.175	0.185	1.000			
15. Elite	0.234	0.192	0.078	0.088	0.059	0.102	0.030	0.028	−0.053	0.005	−0.080	0.417	0.191	−0.002	1.000		
16. logFriends	0.208	0.175	0.076	0.083	0.047	0.068	0.007	0.039	−0.022	−0.005	−0.063	0.353	0.184	0.197	0.489	1.000	
17. logFollowers	0.255	0.180	0.088	0.147	0.094	0.118	−0.023	0.025	−0.028	0.017	−0.107	0.364	0.242	0.215	0.522	0.557	1.000

Table A4. The collinearity diagnostics test

Variable	VIF	Tolerance value
Quantity	1.18	0.846
Aesthetics	1.07	0.938
Clarity	1.03	0.969
ReviewFace	1.03	0.967
Rating	1.06	0.940
Length	1.55	0.645
Readability	1.21	0.829
Date	1.16	0.862
Elite	1.66	0.603
Friends	1.63	0.614
Followers	1.76	0.568

Appendix 3. Robustness check

Table A5. Robustness check using subsamples at two different price levels

Variable	High price	Low price	Moderating effect
Constant	−3.886*** (−38.75)	−3.945*** (−12.41)	−3.961*** (−44.76)
Stars	−0.085*** (−10.79)	−0.084*** (−14.75)	−0.085*** (−18.50)
logLength	0.529*** (47.10)	0.504*** (60.27)	0.513*** (76.52)
logReadability	0.090*** (8.64)	0.103*** (12.94)	0.099*** (15.52)
Date	−0.000*** (−3.03)	−0.000** (−2.56)	−0.000*** (−4.09)
1.Elite	0.373*** (20.09)	0.404*** (30.46)	0.394*** (36.45)
logFriends	0.213*** (44.66)	0.254*** (71.83)	0.239*** (84.33)
logFollowers	0.239*** (40.92)	0.248*** (59.76)	0.245*** (72.44)
logQuantity	0.122*** (8.77)	0.197*** (18.48)	0.210*** (20.28)
Aesthetics	0.336*** (2.88)	0.142* (1.81)	0.153** (1.97)
Clarity	0.125*** (3.08)	0.232*** (7.01)	0.235*** (7.17)
logReviewFace	−0.100*** (−2.90)	−0.049* (−1.90)	−0.051** (−1.99)
logQuantity × 1.Price			−0.111*** (−6.79)
Aesthetics × 1.Price			0.181 (1.28)
Clarity × 1.Price			−0.120** (−2.27)
logReviewFace × 1.Price			−0.050 (−1.16)
Business-fixed effects	Yes	Yes	Yes
α	0.953	0.985	0.976
LR test of $\alpha = 0$	45,680.845 ($p = 0.000$)	91,269.952 ($p = 0.000$)	137,246.084 ($p = 0.000$)
LL	−52,134.432	−106,955.803	−159,142.874
LR χ^2	19,042.823	43,340.616	62,553.108
Pseudo R^2	0.154	0.168	0.164

Notes: *Means the coefficient's significance at 10% level; **means the coefficient's significance at 5% level; ***means the coefficient's significance at 1% level; LR: likelihood-ratio; LL: log likelihood

Variable	Main effect	Moderating effect
Constant	−4.014*** (−47.40)	−4.005*** (−47.26)
Stars	−0.085*** (−18.32)	−0.085*** (−18.31)
logLength	0.516*** (76.85)	0.516*** (76.78)
logReadability	0.098*** (15.35)	0.097*** (15.34)
Date	−0.000*** (−3.67)	−0.000*** (−3.74)
1.Elite	0.396*** (36.64)	0.395*** (36.59)
logFriends	0.240*** (84.43)	0.240*** (84.47)
logFollowers	0.244*** (71.90)	0.244*** (71.83)
logQuantity		
logFoodQ	0.091*** (10.96)	0.091*** (10.95)
logDrinkQ	0.056*** (3.66)	0.057*** (3.74)
LogInteriorQ	0.118*** (11.08)	0.128*** (11.66)
logExteriorQ	0.088*** (4.71)	0.102*** (5.37)
logMenuQ	0.097*** (6.30)	0.096*** (6.15)
Aesthetics	0.296*** (4.31)	0.279*** (4.01)
Clarity	0.203*** (7.76)	0.199*** (7.54)
logReviewFace	−0.096*** (−4.33)	−0.191*** (−5.56)
logFoodQ × logReviewFace		−0.127*** (−3.36)
logDrinkQ × logReviewFace		0.038 (0.46)
logInteriorQ × logReviewFace		−0.033 (−0.76)
logExteriorQ × logReviewFace		−0.232*** (−2.99)
logMenuQ × logReviewFace		−0.158 (−1.56)
Aesthetics × logReviewFace		−0.647* (−1.85)
Clarity × logReviewFace		−0.234* (−1.69)
Business-fixed effects	Yes	Yes
α	0.978	0.977
LR test of $\alpha = 0$	137,745.932 (p = 0.000)	137,540.596 (p = 0.000)
LL	−159,160.381	−159,138.407
LR χ^2	62,518.095	62,562.042
Pseudo R^2	0.164	0.164

Notes: *Means the coefficient's significance at 10% level; **means the coefficient's significance at 5% level; ***means the coefficient's significance at 1% level; LR: likelihood-ratio; LL: log likelihood

Table A6. Alternative operation of review photo quantity

Variable	Main effect	Moderating effect
Constant	−4.192*** (−41.83)	−4.175*** (−41.63)
Stars	−0.087*** (−18.74)	−0.087*** (−18.81)
logLength	0.515*** (76.79)	0.515*** (76.76)
logReadability	0.099*** (15.52)	0.099*** (15.55)
Date	−0.000*** (−2.97)	−0.000*** (−3.00)
1.Elite	0.393*** (36.33)	0.392*** (36.31)
logFriends	0.240*** (84.47)	0.240*** (84.48)
logFollowers	0.245*** (72.41)	0.245*** (72.41)
logQuantity	0.168*** (19.73)	0.168*** (19.77)
Alter_Aesthetics	0.187** (2.53)	0.167** (2.25)
Alter_Clarity	0.020*** (3.47)	0.019*** (3.36)
logReviewFace	−0.093*** (−4.48)	−0.102*** (−4.35)
logQuantity × logReviewFace		−0.109*** (−2.82)
Alter_Aesthetics × logReviewFace		−1.133*** (−3.40)
Alter_Clarity × logReviewFace		−0.068*** (−2.89)
Business-fixed effects	Yes	Yes
α	0.979	0.978
LR test of $\alpha = 0$	137,585.112 (p = 0.000)	137,396.431 (p = 0.000)
LL	−159,194.279	−159,178.323
LR χ^2	62,450.297	62,482.209
Pseudo R^2	0.164	0.164

Notes: *Means the coefficient's significance at 10% level; **means the coefficient's significance at 5% level; ***means the coefficient's significance at 1% level; LR: likelihood-ratio; LL: log likelihood

Table A7.
Alternative operation of review photo quality

Variable	Main effect	Moderating effect
Constant	−3.897*** (−44.70)	−3.888*** (−44.56)
Stars	−0.051*** (−9.87)	−0.051*** (−9.84)
logLength	0.533*** (76.63)	0.533*** (76.60)
logReadability	0.098*** (15.42)	0.098*** (15.45)
Date	−0.000*** (−3.78)	−0.000*** (−3.85)
1.Elite	0.399*** (36.96)	0.399*** (36.93)
logFriends	0.240*** (84.65)	0.240*** (84.68)
logFollowers	0.246*** (72.63)	0.246*** (72.63)
Sentiment	−0.441*** (−14.60)	−0.442*** (−14.62)
Breadth	−0.007 (−0.55)	−0.006 (−0.54)
logQuantity	0.172*** (20.36)	0.174*** (20.53)
Alter_Aesthetics	0.198*** (3.04)	0.167** (2.52)
Alter_Clarity	0.188*** (7.32)	0.179*** (6.92)
logReviewFace	−0.063*** (−3.05)	−0.122*** (−4.78)
logQuantity × logReviewFace		−0.092** (−2.34)
Alter_Aesthetics × logReviewFace		−0.721** (−2.14)
Alter_Clarity × logReviewFace		−0.282** (−2.10)
Business-fixed effects	Yes	Yes
α	0.974	0.973
LR test of $\alpha = 0$	137,125.629 (p = 0.000)	136,956.466 (p = 0.000)
LL	−159,060.453	−159,051.097
LR χ^2	62,717.950	62,736.662
Pseudo R^2	0.165	0.165

Notes: *Means the coefficient's significance at 10% level; **means the coefficient's significance at 5% level; ***means the coefficient's significance at 1% level; LR: likelihood-ratio; LL: log likelihood

Table A8.
Additional control variables

Variable	Main effect	Moderating effect
Constant	−8.215*** (−2.79)	−8.241*** (−2.80)
Stars	−0.084*** (−18.17)	−0.084*** (−18.15)
logLength	0.513*** (76.54)	0.513*** (76.49)
logReadability	0.100*** (15.68)	0.100*** (15.70)
Date	0.001* (1.67)	0.001* (1.69)
1.Elite	0.403*** (37.13)	0.402*** (37.10)
logFriends	0.239*** (83.89)	0.239*** (83.93)
logFollowers	0.246*** (72.66)	0.246*** (72.65)
logQuantity	0.173*** (20.41)	0.174*** (20.59)
Aesthetics	0.169*** (2.60)	0.139** (2.10)
Clarity	0.196*** (7.60)	0.186*** (7.19)
logReviewFace	−0.061*** (−2.95)	−0.118*** (−4.66)
logQuantity × logReviewFace		−0.085** (−2.15)
Aesthetics × logReviewFace		−0.709** (−2.11)
Clarity × logReviewFace		−0.294** (−2.18)
Business-fixed effects	Yes	Yes
Month-fixed effects	Yes	Yes
Year-fixed effects	Yes	Yes
α	0.971	0.970
LR test of $\alpha = 0$	136,378.237 (p = 0.000)	136,208.840 (p = 0.000)
LL	−158,911.787	−158,902.878
LR χ^2	63,015.283	63,033.099
Pseudo R^2	0.165	0.166

Notes: *Means the coefficient's significance at 10% level; **means the coefficient's significance at 5% level; ***means the coefficient's significance at 1% level; LR: likelihood-ratio; LL: log likelihood

Table A9. Month and year fixed effects

Corresponding author
Haipeng Ji can be contacted at: levonhaipeng.ji@connect.polyu.hk