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Show me your face: investigating the effect of facial features in review images on review helpfulness

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Abstract

Images generated by customers have become a critical component of product reviews. For fashion goods, some customers would embed review images in product reviews and disclose their faces when describing their product experiences, while how facial features affect other customers' perceived helpfulness of reviews remains largely unexamined. Drawing upon Information Adoption Model, this paper proposes that face disclosure and positive emotions revealed by facial expressions in product review images positively affect review helpfulness through increased credibility and emotion contagion effect. Specifically, deep convolutional neural networks are deployed to extract facial features from review images, and negative binomial model with product fixed effect is chosen to conduct empirical analyses based on a large-scale review dataset. We conducted propensity score matching to further deal with the selection problem, and the bias of coefficient caused by algorithm classification error is properly addressed. The empirical results and extensive robustness checks strongly support the positive effects of face disclosure and positive emotions. These findings enrich our understanding of how review images affect people's information adoption behavior and provide viable guidance for visual content management on e-commerce platforms.

Keywords Review images · Face disclosure · Emotion contagion · Information adoption model · Review helpfulness

1 Introduction

Online shopping has become a routine practice in everyday life, and people are accustomed to reading online reviews before purchase to assist their decision-making process [1, 2]. Statistics show that 90% of customers read online reviews before

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visiting a business, and 72% of customers say that positive reviews engender their trust in a business.[1] Visual content represented by images and videos has become an indispensable part of product reviews. US digital customers expect an average of about six images and three videos when looking at a product on Amazon or another platform.[2] Many platforms strive to attract new customers by encouraging users to upload images when they are writing product reviews, and therefore visual information is playing an increasingly larger role in affecting consumer choices [3].

Review images are images embedded in product reviews, posted by online customers to express their product usage experiences. Review images enable reviewers to show product details, defects, or express their emotions through visual representation [4]. Furthermore, as review images are generated by peer reviewers rather than retailers, they are more trustworthy than advertisement images provided by retailers [3]. For different product categories, the content of review images demonstrate great variations. For experience goods such as clothes, some customers would post images of themselves wearing the clothes they bought when writing product reviews, as a way of self-presentation and information provision for other potential customers [5]. Furthermore, a high percentage of these images include customers' face identities [6] and give potential buyers an overall impression regarding how the products fit with the reviewers (Fig. 1). Images with face disclosure increase social presense in the review community, and cultivate people's trust towards the reviewer [7]. Among those images that show face identities, some display a positive facial expression, whereas some look neutral or negative. These different emotions may affect the emotional states of other customers, further affect their trust towards the reviewer, perception of the review and finally their information adoption behavior towards the review [8].

Most of previous research on facial features focus more on reviewer avatar images or profile images [9-12]. These images' purpose is to show the identity information of reviewers, and are irrelevant with product details. Differently, review images are aimed at describing customers' purchase experiences, and are more relevant to product-related information, which can potentially affect other customers' evaluation of the focal review, such as review helpfulness evaluation. As helpful reviews facilitate customers' purchase decisions and increase customer's satisfaction level, e-commerce platforms spend great efforts and time identifying helpful reviews from large amounts of user-generated content. Therefore, it is essential to uncover factors of review images that could affect review helpfulness [1, 9, 16]. Despite prior research has documented *positivity bias* and *negativity bias* on the effect of review text sentiment on helpfulness evaluation [16], the impact of facial emotions in review images is largely ignored. Review content takes multiple modalities, and human brain processes images and texts with different mechanisms in that pictures are encoded as imaginal codes and words are represented as verbal codes in the brain [13]. It remains unclear regarding how a new modality of review valence (namely, review images) affect review evaluation differently from review texts. Therefore, research gaps above lead to our central research questions: (1)

1 https://www.invespcro.com/blog/the-importance-of-online-customer-reviews-infographic/

2 https://www.emarketer.com/content/online-shoppers-expectations-for-visual-merchandising-rises-dramatically.

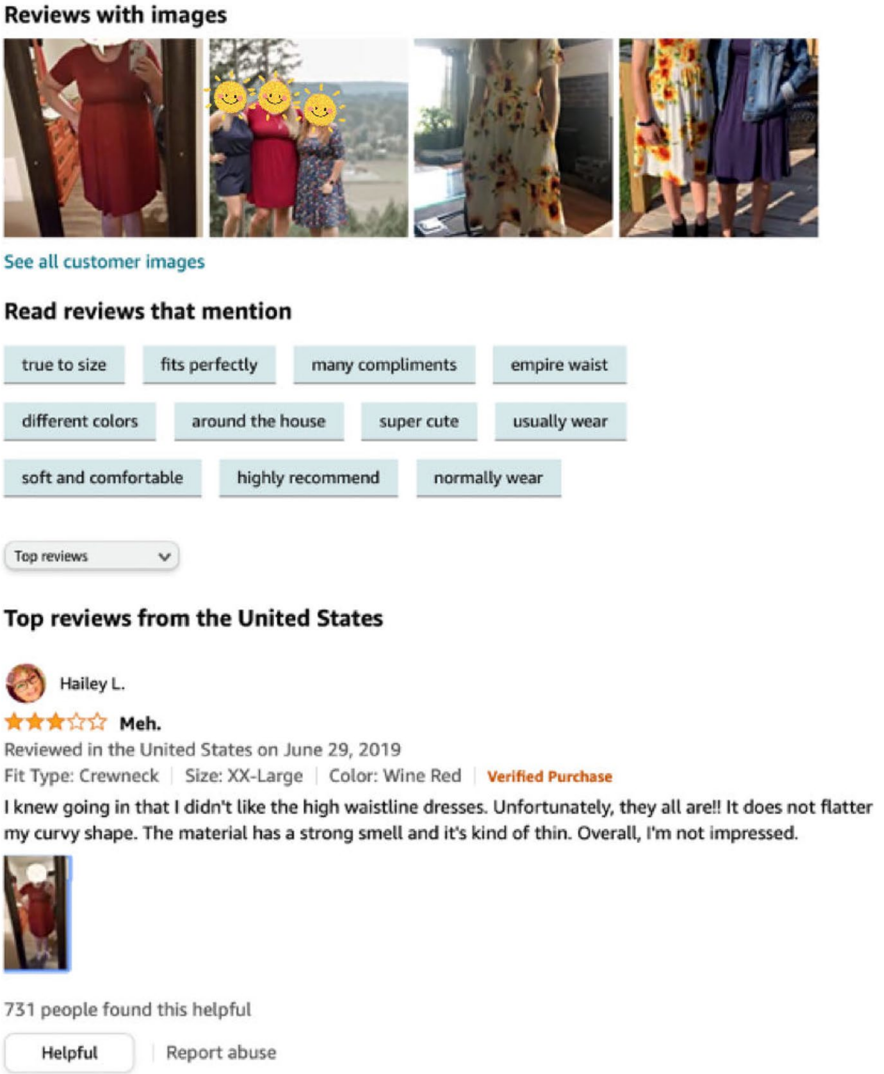

Fig. 1 Screenshot of the product review page. (We masked reviewers' faces in review images to protect users' privacy)

What is the effect of face disclosure in review images on review helpfulness? (2) How do emotions revealed by facial expressions in review images affect review helpfulness?

This paper builds on the Information Adoption Model (IAM) [14] and Emotion Contagion Theory [15] to systematically investigate the effects of facial features embedded in review images on the perceived helpfulness of reviews. We propose that face disclosure positively affects review helpfulness through increased source credibility and social presence, and positive emotions positively affect review helpfulness through emotion contagion effect. Using an extensive dataset on fashion goods from Amazon, a negative binomial model with product fixed effect is chosen to validate our hypotheses empirically. More analyses including propensity score matching, measurement error correction and generalizability on other product categories are conducted to increase the robustness of our findings. All of the hypotheses are supported, enriching our knowledge of what kinds of review images are helpful and how facial features affect evaluation of review helpfulness.

This paper has made several contributions. First, this paper specifically focuses on the characteristics of review images for certain products where customers tend to show their faces in the images, and unravels how granular facial features embedded in review images affect subsequent customers' information adoption behavior. People face high uncertainty in purchasing experience goods such as clothes, and the conclusions of this paper provide suggestions to customers on providing more helpful product reviews. Second, this study angles from Information Adoption Model, and proposes that facial features in review images increase customers' perceived information source credibility, which further increase the perceived helpfulness of the review. Finally, prior research extensively discussed the effect of review valence in the forms of texts and ratings [16-18], while this research focuses on the emotion reflected by reviewer facial expressions. Through consideration of valence signals transmitted through different modalities (i.e., numeric ratings, texts, images), this paper deepens the understanding of how emotions in images differently influence customers' perception of product reviews and provides practical guidance for platform managers on improving the quality of online reviews through visual content management.

2 Related literature

2.1 The effects of review images and reviewer profile images

Prior research has shown that images are rich symbolic systems that are represented in memory differently from linguistic information [19]. Compared with text, images possess high attention-grabbing qualities and are remembered better [20]. Some research (e.g., Zhou and Guo [21] and Osterbrink et al. [22]) found that review images have considerable effects on review helpfulness. A summary of related research on the effect of review images on review helpfulness is provided in Table 1. Most of prior studies mainly focused on the quantity of review images [23, 24] or the types of review images [25, 26] when exploring the impact of review images on helpfulness. Li et al. [27] investigated the effect of review image sentiment on helpfulness in the restaurant context, and image sentiment is measured on the image itself without consideration of facial features. In contrast, we focus on the facial features revealed by customers in review images, which is largely ignored in previous studies.

Facial features in images considerably affect people's perceptions and behaviors [31]. According to social presence theory, a face identity in the image signifies the existence of another person, thus cultivating more trust when potential customers

Table 1 Literature review on review images and helpfulness

	Image-related factors	Theoretical lens	Major findings
Cheng & Ho 2015 [23]	Number of review images	Elaboration likelihood model (ELM)	More review images make readers feel that the review is more practical and useful
Filieri et al. 2018 [24]		Cognitive elaboration; Cue Diagnosticity	Extreme hotel reviews are more helpful with additional review images
Lee, 2018 [29]		Source credibility	Review images have small but significant positive effect on review helpfulness
Osterbrink et al. 2020 [22]		Information processing; text-image interaction	Images have a significant positive effect on helpfulness of reviews of search goods, and this is especially true in case of short and ambiguous reviews
Yang et al. 2017a [25]	Number of physical environment images; Number of food & beverage images	Dual coding theory; review presentation formats	Review images contribute to review usefulness, which is mediated by review enjoyment
Yang et al. 2017b [26]	Types of review photos	The heuristic-systematic model (HSM)	There is a significant impact of images on helpfulness, especially for negative reviews
Ma et al. 2018 [28]	Review image implicit features	–	User-provided photos complement textual contents in predicting review helpfulness
Li et al. 2021 [30]	Review image with guest room objects; Review image with food & beverage objects	Media richness theory	Review images showing guestroom objects are rated as more helpful than those showing food & beverages; the positive effect of review images is especially prominent for hotels with lower prices and negative reviews
Li et al. 2022 [27]	Review image sentiment; Number of review images	Dual coding theory; text–image congruence	Reviews with photos are more useful; a U-shaped relationship exists between review photo sentiment and review usefulness, which is strengthened by the number of review photos
This study	Review images; Review images with faces; Facial expression of review images	Information Adoption Model; Emotion Contagion Theory	Review images with human faces and positive facial expression show significant positive impacts on review helpfulness

evaluate a product [7]. Emotions revealed in facial expressions can influence users' decisions to share knowledge with others [32], can be leveraged to provide fashion recommendations [33], and can dissimilarly affect people's attitudes to a brand [34]. In the context of online platforms, some research discussed the effect of facial features in reviewer profile images or avatar images [9-11]. Reviews with profile images are perceived as more helpful with two main functions when accompanied by texts [9], namely, to provide information (i.e., the informative function) and to generate affective responses (i.e., the affective function). Lee et al. [11] drew upon attribution theory, discussed the interactions of facial expressions of user avatars and review valence. Chen et al. [10] investigated how the emotions of reviewer avatar affect review helpfulness differently depending on whether a group of people or a single person is in the review image. Barnes and Kirshner [12] focused on the facial features of profile images and discussed their effect on housing prices on Airbnb. Although the complex effect of facial features has been investigated from various perspectives, most of them focus on the features of reviewer avatar images and profile images [9, 12]. For products such as clothes, facial features embedded in review images [4] are closely tied to a specific product, which affect users' perception in a different manner from those profile or avatar images. Therefore, given the research gaps and practical necessity, it is worthy of investigation regarding how facial features in review images are perceived by potential buyers.

2.2 Review helpfulness

A helpful customer review is defined as peer-generated product evaluation that facilitates customers' purchase decisions, consistent with previous conceptualizations of perceived diagnosticity [35]. There are two streams of literature on review helpfulness, with one focusing on predicting the helpfulness of a review [37], whereas the other focuses on detecting novel factors that may affect review helpfulness [17, 38]. This paper mainly discusses the second stream, which is more relevant to our research.

A thorough review of factors that affect review helpfulness [17] manifests in the following aspects, including textual features, rating, time, and other contextual variables. Text-related factors, such as readability [38], review length [35] and sentiment [36], have been extensively investigated. With respect to sentiment of review texts, positive or negative sentiments are more helpful than neutral ones [27]. Anxiety and anger, are two discrete negative emotions embedded in review texts, and they generate different effects on helpfulness in that anxious reviews are perceived to involve higher amount of efforts in writing the review [16, 39]. Yu et al. [40] uncovered the mechanism of emotions' effect and proposed that discrete emotions affect review helpfulness through perceived processing fluency. With respect to review rating, positivity bias and negativity bias (people tend to rate positive or negative reviews as more helpful) [16, 36] have been validated, and the effects could be dependent on customers' initial beliefs [18]. Review time is highly relevant because early reviews have the greatest customer reach and consequently, are more likely to accumulate more helpful votes [41]. Furthermore, moderators such as temporal and social cues

[42], review platform [17], and product type [43] all play remarkable roles in affecting review helpfulness. To summarize, most of the above research focuses on textual and structural features of reviews, and these factors will serve as control variables in our proposed model.

3 Hypothesis development

Customers' adoption and recognition of online reviews is a typical process of information adoption. The Information Adoption Model [14] proposed by Sussma and Siegal is taken as the overarching theoretical framework in this paper. IAM highlights the salient role of information usefulness in affecting users' information adoption and further postulates that information usefulness is reliant on two factors, namely, information quality and information source credibility. The quality of information, serving as the core factor for individuals' cognitive elaboration in a persuasive communication, determines the degree of informational influence [44]. Source credibility provides further cues for individuals to evaluate the trustworthiness of the information provider [45].

In our research context, potential customer's "communication" with the online reviews entails a process of review helpfulness evaluation. According to IAM, review helpfulness evaluation depends on the quality of review content and the credibility of reviewers [14]. From a quality perspective, as online reviews mainly serve customer's product evaluation and decision-making purpose [1], we thereby propose that the information quality of reviews refers to whether the specific review can help customers to evaluate the products when they encorter uncertainties (e.g., product quality and fit uncertainty) during online shopping from a functional view [46, 47]. From a credibility perspective, prior studies have repeatedly established the link between trust among different parties and interested outcomes [48]. In the online shopping context, whether the reviewer is credible acts as another important factor that determines helpfulness evaluation.

3.1 The effect of review images

Prior literature has repeatedly established the positive link between review images and review helpfulness [22, 23, 30]. As the saying goes, a picture is worth a thousand words. Compared with review texts, review images have perceptual and persuasive advantages in illiciting purchases [49] because they possess high attention-grabbing qualities and provide more detailed information through the provision of visual cues [20]. For experience products, such as clothes, with the reviewer's product trial images, potential buyers can obtain more cues on person-product fit from these images, which will provide potential buyers with more information about the dress-on effect of the specific product and let them better evaluate whether the specific product fits them or not. Prior research in live-stream selling has also found that customers' perceived physical characteristic similarity with the broadcaster cultivated via clothes try-on efficiently reduces customers' perceived product fit uncertainty [50]. Based on the above elaboration, we have Hypothesis 1.

Hypothesis 1 Product reviews with review images are more helpful than product reviews without review images.

3.2 The effect of face disclosure in review images

Following IAM, review images with customer face disclosure not only complement review texts with respect to product-related information but also make the identity of the reviewer public by presenting to the public what the reviewer looks like. Most of the review images with face disclosure show reviewer themselves, since disclosing other people's photos without permission is inappororiate behavior, which makes the review less likely to be a fake review because people who aim to post fake reviews have no incentive to disclose their identity information. In other words, the cost of posting a fake review with face disclosure is much higher than posting a fake review without face disclosure. Consequently, review images with faces serve as a powerful signal indicating the credibility of the review source, leading to increased information usefulness perception [14].

From another perspective, the presence of reviewer's face in the image could increase the awareness of the other person and create the impression of a face-to-face communication in the online review community [7], making potential buyers feel like they are communicating directly with the reviewer on product experiences. Cyr et al. [7] propose that the disclosure of facial features induce users to perceive a website as having more social presence and being more trustworthy. Meanwhile, as facial features are more private information, reviewers disclosing their facial images in reviews will help to form intimate relationships between reviewers and potential customers [51]. Therefore, in the online review system, reviewers with face disclosure are perceived by others as more trustworthy, and the increased credibility of the review source further increases the helpfulness of the review based on the IAM, which leads to Hypothesis 2.

Hypothesis 2 Product reviews that disclose reviewer faces are more helpful than product reviews without face disclosure.

3.3 The effect of emotions in reviewer face dislosure

Reviewers show different emotions in review images with face disclosure. Expressing emotions is a salient characteristic of human communication. Emotions describe how people think and feel and their degree of pleasure or displeasure [52], and can be reflected in people's facial expressions. A communication process can be easily affected by either side's emotional states. Emotion contagion [15] is defined as the tendency to mimic and synchronize expressions, vocalizations, postures, and movements automatically with those of another person and consequently, converge emotionally with that person. Emotion contagion is commonly observed in people's interactions, where one person's emotions and related behaviors directly trigger similar emotions and behaviors in other people [53].

A positive facial expression in review images reflects the happy state of the reviewer. According to emotion contagion [15, 53], a reviewer's happy emotion reflected by a positive facial expression could be transferred to potential buyers. As smile is the universal language of kindness, a smile in the review image transmits the positive emotional state to the other customers, and increase the trust between strangers [54]. Furthermore, the affectively loaded product review could exert an influence on the customers' mental processes [55, 56], which eventually affect their perception of the review information provided. In the online review context, customers are usually not familiar with reviewers, upon which positive emotions (e.g., happiness) triggered by positive facial expressions bring other customers to a similarly positive emotional state, and at the same time increase their trust perception towards the reviewers. Therefore, customers perceive the product reviews with positive emotions as more credible, and the increased source credibility further enhances the helpfulness of reviews perceived by other customers [14]. Based on the above elaboration, this paper proposes the following hypothesis.

Hypothesis 3 Product reviews that show positive emotions in facial expressions are more helpful than product reviews without positive emotions in review images.

4 Research context and feature extraction

To empirically answer our research questions, we chose Amazon platform as our main context. Specifically, we collected review data generated for all the products in the category of Women Casual Dresses. Women dresses are typical experience goods, for which product reviews are valuable information sources for customers to make purchase decisions. Specifically, all products were collected in this category with information including product characteristics and corresponding product reviews generated from the very beginning to the time of data collection. Figure 1 presents a screenshot of the product review section on the platform. Review images are embedded not only in the reviews but also in a separate space at the top of the review page, indicating their prominent business value to the platform. In the several review images shown in Fig. 1, it could be observed that some images disclose faces, while some not. The heterogeneity of review images provides opportunity for us to disentangle the effect of facial features on review helpfulness.

4.1 Facial feature extraction

To detect faces from large-scale review images, Multitask Cascaded Convolutional Networks (MTCNN) framework [57] was deployed. This framework is based on the convolutional neural network and consists of three sub networks. First, candidate windows are generated through the fast proposal network (P-Net). Second, the candidates are refined through a refinement network (R-Net). Third, the final bounding box positions are generated through the output network (O-Net). The details of the model are described in Appendix A. Note that a well-trained model is provided by Zhang et al. [57], therefore we could directly deploy the model to our dataset. We asked two volunteers to evaluate the classification performance of the algorithm on a random sample of our dataset (200 images), and compared their manual labels with the labels generated by the algorithm. Results showed that the overall accuracy is 94%, with precision and recall for the positive class 84.6% and 100% respectively.

Individuals' facial expressions can reflect their emotions. Through the emotion API provided by Baidu AI open platform,[3] we were able to conduct emotion classification for reviewer faces detected by MTCNN. The API can detect nine emotions, namely, happy, sad, neutral, disgust, surprise, fear, anger, grimace and pouty. Given that the last four categories are rare in our research context, and some emotions are difficult to classify even for human beings (such as neutral, sad), we further reorganized them into two main categories: positive emotions (happy) and other emotions (including sadness, neutral, etc.). We evaluated the classification performance on our dataset following the same procedure as above. By comparing the manually labelled data and the results generated by the emotion API, we conclude that the precision and recall for the positive class are 84.4% and 96.4%, with overall accuracy being 87.1%. Overall speaking, the performance of these two visual feature extraction algorithms are acceptable. In Sect. 7.3, we further considered the effect on estimated coefficient because of the measurement error of face detection and emotion classification.

4.2 Textual feature extraction

In addition to visual features, textual features of product reviews also significantly affect review helpfulness [27]. We employed the text mining tool Linguistic Inquiry and Word Count (LIWC) [47] to extract sentiments from review texts, which is widely accepted in social science research [58]. In addition to positive or negative sentiments, text readability could potentially affect review helpfulness as well [59], therefore we controlled the Flesch reading ease score as measurement of readability in our model, which is calculated using Eq. (1).

$$readbility = 206.835 - 1.015\left(\frac{total\,words}{total\,sentences}\right) - 84.6\left(\frac{total\,syllables}{total\,words}\right) \tag{1}$$

5 Summary statistics

The description of variables and summary statistics are shown in Tables 2 and 3, respectively. The whole dataset consisted of 224,858 reviews, with average rating 3.96 stars. Consistent with the rating statistics, the average positive sentiment score was much higher than the average negative sentiment score in the review texts. Note that

[3] https://ai.baidu.com/tech/face/detect.

Table 2 Variable descriptions

	Variable	Definition
DV	Helpfulness	Number of helpful votes of a product review
IV	Image	Whether a product review contains review images
	Face	Whether a review image contains reviewer face identity
	ImgPosEmo	Whether a review image contains positive facial expressions
Control Variables	ReviewWC	Word count of review body text
	TitleWC	Word count of review title
	ReviewTime	Number of days elapsed from review post time to data collection time
	Rating	Rating given by the reviewer
	TextPos	Positive sentiment score embedded in texts, calculated by LIWC
	TextNeg	Negative sentiment score embedded in texts, calculated by LIWC
	Readability	Flesch reading ease score
	PageIndex	The position a review appears on the platform, denoted as the page index a review appears in all of the product reviews
	Product_id	Identification number of each product

the variable *PageIndex* refers to the position of a review on the platform, which is different from the chronological order of a review, as platforms usually rank the reviews by relevance according to some private algorithms. Reviews with helpful votes and reviews with review images accounted for 27.42% and 4%, respectively. Of all reviews containing review images, images with face identities accounted for 45%, and review images with positive emotions accounted for 56% of all the images that disclose faces.

The distributions of review word count, review title word count, review time, and page index are all right-skewed with a long tail. Therefore, a log transformation of these variables was conducted before estimating the main model. The correlations among variables are less than 0.5 and variance inflation factor (VIF) is less than 5, as shown in Table 4, indicating that no collinearity problem exists.

6 Research model and empirical results

The choice of our model specification are based on two aspects. First, the key outcome variable, number of helpful votes, belongs to count data. Second, the distribution of the outcome variable demonstrates typical overdispersion characteristics (variance much larger than the mean), as shown in Table 3, and the results of the likelihood-ratio test show that dispersion parameter alpha is greater than zero. These two facts indicate that a negative binomial regression model should be chosen as our main model instead of a Poisson model, which is consistent with prior literature [1, 21]. We further conducted Hausman test to determine the choice of fixed effect or random effect model. The results rejected the null hypothesis and justified the choice of a fixed effect model (Chi-square = 1235, p_value = 0.0000). The main model is shown in Eqs. (2)–(3), in which α denotes the dispersion parameter.

In addition to the main variables of interest, textual features that could affect review helpfulness were added to the model, including word count statistics, text sentiments, and readability [17, 35, 38]. Considering that reviews appearing in different positions have different probabilities of being observed and voted, *PageIndex* is also included and controlled in the model, which refers to the actual position of a review appearing on the platform. Furthermore, linear and quadratic term of rating and review time were included, as previous studies have demonstrated that they are related to review helpfulness [17]. Finally, α_i indicates product fixed effect, aiming to control potential unobserved product characteristics that may affect the outcome. Through methods above, we make sure that the model selection is appropriate and the related variables are all controlled. In Sect. 7, we discuss other robustness check methods to further increase the validity of our findings.

$$\Pr\left(helpfulness = y_i | u_{it}, \alpha\right) = \frac{\Gamma\left(y_i + \alpha^{-1}\right)}{\Gamma\left(\alpha^{-1}\right)\Gamma\left(y_i + 1\right)}\left(\frac{1}{1 + \alpha u_{it}}\right)^{\alpha^{-1}}\left(\frac{\alpha u_{it}}{1 + \alpha u_{it}}\right)^{y_i} \tag{2}$$

$$\begin{aligned} u_{it} = \exp(&\beta_0 + \beta_1 Image + \beta_2 Face + \beta_3 ImgPosEmo + \beta_4 LogReviewWC \\ &+ \beta_5 LogTitleWC + \beta_6 LogReviewTime_{it} + \beta_7 Rating + \beta_8 Rating^2 \\ &+ \beta_9 LogPageIndex + \beta_{10} TextPos + \beta_{11} TextNeg + \beta_{12} Readability + \alpha_i + \varepsilon_{it}) \end{aligned} \tag{3}$$

The estimation results of our model are presented in Table 5. The first three hypotheses were tested with stepwise regression. First, a baseline model was estimated with all the control variables, as shown in Column (1). Rating has a U-shape effect on review helpfulness, indicating that extreme ratings are perceived as more helpful, which is consistent with prior studies [35]. Text sentiments have no significant effect after adding image-related variables. With respect to time, an earlier review tends to have more helpful votes owing to its longer exposure time on the platform. Longer reviews and reviews with higher readability scores are perceived to be more helpful. Then, the variable of *Image* was added to the model. The results from Column (2) indicate strong support

Table 3 Descriptive statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Helpfulness	224,858	1.300	8.386	0	872
ReviewWC	224,858	31.192	37.021	0	1,365
TitleWC	224,858	4.331	3.711	0	31
TextPos	224,858	13.767	17.726	0	100
TextNeg	224,858	0.936	4.089	0	100
Readability	224,858	88.314	21.696	−386.38	206.835
ReviewTime	224,858	424.684	290.778	58	2938
Rating	224,858	3.962	1.325	1	5
PageIndex	224,858	19.707	34.512	1	292
Image	224,858	0.040	0.195	0	1
Face	224,858	0.018	0.134	0	1
ImgPosEmo	224,858	0.010	0.098	0	1

Table 4 Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Helpfulness	1.000								
(2) ReviewWC	0.174	1.000							
(3) TitleWC	0.028	0.285	1.000						
(4) ReviewTime	0.086	0.077	– 0.036	1.000					
(5) Rating	0.027	0.002	– 0.088	0.012	1.000				
(6) PageIndex	0.081	0.034	– 0.007	0.262	0.068	1.000			
(7) TextPos	– 0.050	– 0.322	– 0.241	– 0.037	0.348	0.002	1.000		
(8) TextNeg	– 0.006	– 0.015	– 0.008	– 0.006	-0.237	– 0.018	– 0.123	1.000	
(9) Readability	– 0.002	– 0.076	– 0.039	– 0.012	-0.014	– 0.004	– 0.059	– 0.130	1.000

for H1, and review images have a significantly positive effect on review helpfulness, supporting previous findings [27]. The additive effects of facial features (i.e., face disclosure and emotion) are investigated in Column (3) and (4). From Column (3), the impact of face disclosure is positive and significant, and the coefficient of 0.3243 means that face disclosure in review images increases the log count of helpful votes by 0.3243. Furthermore, consistent with H3, the effect of positive emotions is also significantly positive, and the coefficient of 0.0661 indicates that the appearance of positive emotions further increases the log count of helpful votes by 0.0661.

The above estimation was conducted on the full review dataset. One concern is that the appearance of review images is not fully random and there may be some variables that affect the appearance of review images as well as helpfulness. To further address this concern, we divided the dataset into the treatment group (reviews with images) and control group (reviews without images), and conducted propensity score matching on the two groups to make sure that the other variables on the two groups have no significant differences. Balance check results are presented in Appendix B, which show that the two groups are not significantly different on all of the control variables after matching. The estimation results with matched dataset in Column (5) further confirmed previous findings.

7 Robustness checks

To further prove the robustness of the above estimation results, more discussion is provided in this section to illustrate that our main results remain similar when accounting for other product categories, measurment error, and alternative variable measurements.

Table 5 Main estimation results

Variables	Full dataset				Matched dataset
	(1) Control	(2) Image	(3) Face	(4) Emotion	(5) Emotion
Image		2.2263***	2.0917***	2.0916***	2.0052***
		(0.0116)	(0.0142)	(0.0142)	(0.0179)
Face			0.3243***	0.2897***	0.2305***
			(0.0172)	(0.0214)	(0.0243)
ImgPosEmo				0.0661***	0.0511*
				(0.0241)	(0.0271)
LogReviewWC	0.7069***	0.5740***	0.5796***	0.5798***	0.4559***
	(0.0055)	(0.0053)	(0.0053)	(0.0053)	(0.0097)
LogTitleWC	− 0.0558***	− 0.0045	− 0.0083	− 0.0085	− 0.0048
	(0.0073)	(0.0070)	(0.0070)	(0.0070)	(0.0119)
LogReviewTime	2.1493***	2.6348***	2.6475***	2.6468***	2.7358***
	(0.0212)	(0.0225)	(0.0225)	(0.0225)	(0.0403)
Rating	− 0.5090***	− 0.4492***	− 0.4528***	− 0.4522***	− 0.3052***
	(0.0176)	(0.0170)	(0.0170)	(0.0170)	(0.0362)
Rating^2	0.0801***	0.0685***	0.0681***	0.0680***	0.0500***
	(0.0027)	(0.0026)	(0.0026)	(0.0026)	(0.0052)
LogPageIndex	− 0.7723***	− 0.7315***	− 0.7292***	− 0.7290***	− 0.5488***
	(0.0108)	(0.0113)	(0.0113)	(0.0113)	(0.0193)
TextPos	0.0019***	− 0.0005	− 0.0003	− 0.0002	0.0006
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0011)
TextNeg	0.0044***	0.0016	0.0017	0.0017	− 0.0038
	(0.0015)	(0.0015)	(0.0014)	(0.0014)	(0.0044)
Readability	0.0014***	0.0016***	0.0016***	0.0016***	0.0052***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0005)
Observations	224,858	224,858	224,858	224,858	47,703
Product FEs	Yes	Yes	Yes	Yes	Yes
Log likelihood	− 209,937	− 210,116	− 209,940	− 209,937	− 65,124

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

7.1 Discussion on the mechanism of image emotion

Given the results above, one concern is that image emotion is a proxy variable of reviewer's satisfaction with the product, therefore the uncovered effect is just similar to the effect of text sentiment or rating theoretically, which undermines the contributons of this paper.

To address this concern, Table 6 demonstrates the correlation of rating, text sentiment and image emotion, which indicates that there are positive correlations among these three types of variables. However, the correlation between image positive emotion and rating (text sentiment) is 0.084 (0.047), which is much smaller than the correlation between rating and text sentiment. In other words,

Table 6 Correlation matrix of rating, text sentiment and image emotion

	Rating	TextPos	TextNeg	ImgPosEmo
Rating	1.000			
TextPos	0.160	1.000		
TextNeg	− 0.1841	− 0.106	1.000	
ImgPosEmo	0.084	0.047	− 0.025	1.000

whether the reviewer shows a smile in the review image is not always consistent with the satisfaction level indicated by review rating. Further evidence is shown in the 2×2 Contingency Table of Review Rating and Review Image Emotion (Table 7). In the 177 reviews that have low ratings, 62 images display positive emotions, and in the 3216 reviews that have high ratings, 1444 images display non-positive facial expressions. These statistics imply that people could display positive (non-positive) expressions even if they are not (are) satisfied with the product. The reason could be that they want to leave a good impression on others out of their self-presentation concern or their own personal habits [4, 6]. We regard these facts as further evidence showcasing our proposed mechanism of emotion contagion. That is, customers can be simply influenced by the smile of the reviewers to give the reviews a helpful vote. In other words, the emotions in review images affect people's evaluation of a review differently from review texts and ratings both theoretically and empirically, which further emphasizes the necessity and critical importance of investigating how emotions in review images affect review evaluation.

7.2 Generalizability to other product categories

To validate the generalizability of our findings to other similar product categories, we chose another type of clothes, Women Cardigans, to conduct the same model estimations. This is also a type of experience goods, and certain percentage of customers like to share images with their facial features disclosed in product reviews. We extracted features including time, rating, textual features, and visual features, and conducted analyses using both the whole dataset and the matched dataset after propensity score matching. The results in Table 8 remained robust that both face disclosure and positive emotions have positive effects on helpful votes.

7.3 Measurement error correction

In our model specification, *Face* and *ImgPosEmo* are both variables generated from deep learning based classification algorithms. Considering that these algorithms are not 100% accurate, these variables with measurement errors may further bring bias to the estimated coefficients in the main model. Therefore, we conducted analyses using a data-driven correction method, MC-SIMEX, by referring to prior literature [60]. This method requires only information of mis-classification matrix, and

Table 7 2×2 Contingency table of review rating and review image emotion

Rating	Image non-positive emotion (%)	Image positive emotion (%)	Total (%)
Low rating (1–3 star)	115 (3.39)	62 (1.83)	177 (5.22)
High rating (5 star)	1444 (43.56)	1772 (52.23)	3216 (94.78)
Total	1559 (45.95)	1834 (54.05)	3393 (100)

demonstrates great performance under different econometric specifications. The R code for MC-SIMEX correction is provided in Appendix C. From the results in Column (1) of Table 9, it could be observed that the coefficients of the two misclassified variables, *Face* and *ImgPosEmo* after correction are larger in absolute value than previous results, which are also consistent with prior literature that the effect of misclassified variables are underestimated with the existence of measurement error [60].

7.4 Alternative measurements: emotion and readability

In this subsection, we discuss alternative measurements of key variables in our model specification. Firstly, with respect to emotion in review images, previously we used a dummy variable, which equals 1 if review images have at least one positive face in a specific review. An alternative measurement of postive emotion is to count the number of happy faces in a review, because there could be multiple faces or images appearing in a single review. The number of positive faces can be regarded as a proxy of postive emotion intensity. Consistent findings are obtained with this alternative measurement, as the coefficients of the three image-related variables remain significantly positive, as shown in Column (2) (Table 9).

Secondly, with respect to readability, we replaced Flesch reading score with another metric that measures readability, which is Gunning Fog Index. Gunning Fog Index is calculated by Eq. (4) and it represents the years of formal education a person needs to understand the text on the first reading. The larger score it is, the more difficult for the texts to understand. The results shown in Column (3) of Table 9 further confirm our main estimation, and the negative coefficient of readability means that the more easier to read, the more helpful votes a review could obtain.

$$GFI = 0.4 \times (total\,words/total\,sentences + 100 \times total\,complex\,words/total\,words) \tag{4}$$

8 Conclusions, implications, and future work

This paper focuses on the effects of facial features in review images on review helpfulness. Through the theoretical lens of the Information Adoption Model and Emotion Contagion Theory, this work proposes that face disclosure, and positive emotions in review images increase review source credibility, and therefore increase the perceived review helpfulness. Leveraging a large-scale real-world dataset, deep learning based algorithms and advanced econometric models are

Table 8 Estimation results on women cardigan product category

Variables	(1) Full data		(2) Matched data	
Image	4.0449***	(0.0773)	3.3910***	(0.0671)
Face	0.6805***	(0.1612)	0.4682***	(0.1158)
ImgPosEmo	0.8403***	(0.2274)	0.2980*	(0.1646)
LogReviewWC	3.5431***	(0.0440)	2.7853***	(0.0891)
LogTitleWC	− 0.1256**	(0.0550)	− 0.0532	(0.1034)
LogReviewTime	− 29.3618***	(0.3514)	− 29.2316***	(0.7295)
Rating	− 1.1573***	(0.0552)	− 0.8223***	(0.1006)
$Rating^2$	0.1498***	(0.0084)	0.1209***	(0.0156)
TextPos	0.0062***	(0.0014)	0.0260***	(0.0039)
TextNeg	0.0180***	(0.0046)	0.0343***	(0.0100)
Readability	0.0029	(0.0037)	0.0209***	(0.0081)
Observations	108,813		12,432	
Product FEs	Yes		Yes	
Log likelihood	− 57,537		− 13,974	

Table 9 Robustness checks

Variables	(1) MC-SIMEX correction		(2) Emotion intensity	(3) Gunning fog index
	Predicted	Corrected		
Image	2.6039***	2.5500***	2.0058***	2.0033***
	(0.0063)	(0.0126)	(0.0179)	(0.0179)
Face	0.2656***	0.2925***	0.2251***	0.2298***
	(0.0070)	(0.0290)	(0.0230)	(0.0243)
ImgPosEmo	0.0825***	0.1361**		0.0508*
	(0.0075)	(0.0425)		(0.0271)
ImgPosEmoIntensity			0.0524***	
			(0.0193)	
Readability	0.0082***	0.0082***	0.0052***	− 0.0075***
	(0.0002)	(0.0002)	(0.0005)	(0.0019)
Controls	Yes	Yes	Yes	Yes
Observations	47,703	47,703	47,703	47,703
Log likelihood	− 190,069		− 65,122	− 65,164

MC-SIMEX does not provide log likelihood statistics. We use Poisson model instead of negative binomial model in Column (1) because the MC-SIMEX method does not support negative binomial model

deployed to empirically answer the research questions. The estimation results and extensive robustness check methods validate our hypotheses.

Theoretically, this paper expands the boundary of existing research on review images and unravels the granular effect of facial features in product reviews.

Visual content has become an indispensable part in online community and have received increasing attention by retailers and platforms. This paper extensively discusses the role of face disclosure and positive emotions in increasing information credibility and promoting trust, and validates their positive effects on review helpfulness with ample empirical evidence. These results deepen our understanding of how facial features play a critical role in customers' review evaluation process. Moreover, through in-depth analyses, we illustrate the uniqueness of image emotions that differs from review ratings or textual content, demonstrating the superior role of visual content over other review modalities, which collectively emphasizes the necessity of investigating visual UGC's impact.

Practically, our findings provide rich managerial insights for platform managers, retailers, and reviewers on the value of review images with detailed results. First, this paper strengthens existing findings that review images as a type of visual UGC can significantly increase review helpfulness and deserve special attention from managers and retailers. Additionally, this paper offers guidance on what kind of review images are more helpful. Mainly focusing on product reviews of fashion goods, this research shows that review images disclosing reviewers' face identity and showing a positive facial expression are proven more helpful. Face disclosure and positive emotions can illicit more trust from customers, create more social presence and transmit the positive emotion to others. Therefore it is recommended that reviewers be encouraged to disclose more personal information and show positive emotions in images to increase information adoption by other customers. Our findings also provide implications for platform managers on maximizing of value of online reviews through visual content management.

Several directions merit further investigation. First, our empirical results are based on fashion products. Fashion goods are typical experience goods that customers like to try on and show their facial features in review images. However, for products such as electronics, reviewers may rarely post images disclosing their face identities. Therefore, our conclusions do not apply to all the product categories on e-commerce platforms, despite that this paper shows certain generalizability for other similar experience products. Second, this paper mainly examines facial features in review images and did not consider other image related factors. It would be an interesting topic to enlarge the research scope and investigate the effect of other visual factors (such as image quality) on review helpfulness in future research. Lastly, the order of a review affects review helpfulness, and review helpfulness further affects how platforms rank a review, which constitutes a dynamic process. Further investigations may consider modeling the dynamic process to capture the effect of review order with a finer granularity.

Appendix A: Details of the face detection model

The MTCNN [57] framework is adopted to detect faces from review images (Fig. 2). This framework is a cascaded convolutional neural network structure that performs a face detection task in three steps. In the first step, the input image is fed into the proposal network, which consists of three 3×3 convolutional layers and a max pooling

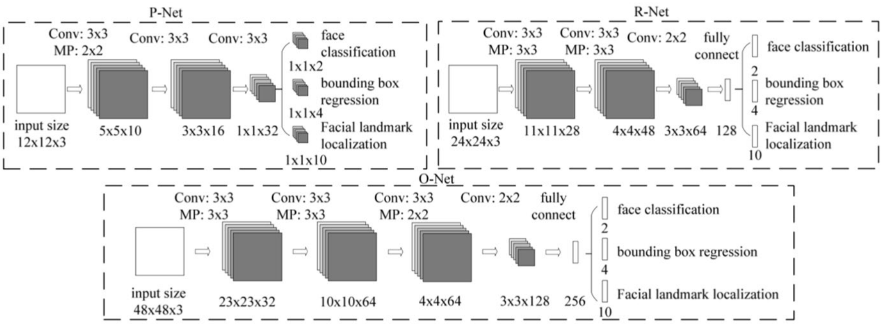

Fig. 2 Face detection framework (Adopted from Zhang et al. [58])

layer. The proposal network generates some candidate boxes that may contain human faces as well as bounding box locations. In the second step, the generated candidates are fed into the refine network, which consists of three convolutional layers and a fully connected layer, and most of the false candidates are rejected. In the last step, the output network performs a supervised learning and outputs the final face detection results, displaying the location of bounding boxes and facial landmarks.

The loss function of this model is composed of three parts, namely, loss for face detection, bounding box regression, and landmark localization. Different weights are placed on these three losses in different sub networks, and a weighted sum is deployed to form the final objective function.

Appendix B: Balance check results of propensity score matching

	Before matching				After matching			
	Treat	Ctrl	t	p-value	Treat	Ctrl	t	p-value
Rating	4.39	3.94	31.33	0.00	4.39	4.38	0.71	0.48
LogPageIndex	0.88	0.87	1.82	0.07	0.88	0.89	−0.20	0.84
LogReviewTime	2.45	2.54	−26.51	0.00	2.45	2.45	0.57	0.57
LogReviewWC	3.74	2.93	71.18	0.00	3.74	3.74	0.01	0.99
LogTitleWC	1.59	1.49	15.97	0.00	1.59	1.59	0.31	0.76
TextPos	9.31	13.90	−23.93	0.00	9.31	9.29	0.10	0.92
TextNeg	0.71	0.95	−5.32	0.00	0.71	0.72	−0.47	0.64
Readability	88.80	88.29	2.17	0.03	88.80	88.72	0.30	0.77

Appendix C: R code for MC-SIMEX correction

```
library(simex)
library(MASS)
library(cabootcrs)
# read in the dataset
data = read.csv()
# convert to factor variable
data$face_dummy<- factor(data$face_dummy)
data$emotion_dummy<- factor(data$emotion_dummy)

#specify the misclassification matrix of face dummy variable
mc.face<-matrix(c(0.91,0.09,0,1),nrow=2)
dimnames(mc.face)<-list(c("0","1"),c("0","1"))

#specify the misclassification matrix of emotion dummy variable
mc.emotion<-matrix(c(0.73,0.27,0.04,0.96),nrow=2)
dimnames(mc.emotion)<-list(c("0","1"),c("0","1"))

#run the regression that contains misclassified variables, and choose the
# appropriate model faimily
naive = glm(helpful~img_dummy+face_dummy+emotion_dummy+rating+rating_2
            +log_review_time +log_page_no+text_pos+text_neg+readability+
            log_title_word_count+log_review_word_count,family=(),
            data=data,x=T,y=T)
summary(naive)

#perform MC-SIMEX correction by calling mcsimex() function
model.simex = mcsimex(naive,SIMEXvariable=c("face_dummy","emotion_dummy"),
              mc.matrix = list(face_dummy = mc.face, emotion_dummy=mc.emotion))
summary(model.simex)
```

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Declarations

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