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Abstract

Determinants of online consumer's purchase decisions are of long-term interest to researchers and practitioners. Since product photos directly aid consumers' understanding of products, retailers often put a lot of effort into polishing them. However, there is limited research on the impact of product photos on purchase decisions. Most previous studies took an experiment-based approach, which delivered strict theories on some aspects of product photos.

This research takes advantage of image-processing techniques to study product photos' impact. These techniques allow us to investigate a large set of photo characteristics simultaneously in an empirical study. To rule out possible confounding factors, we collect a dataset from a social shopping Website, which has a simple interface allowing users to judge products mainly based on their photos. We examine product photo characteristics from the aspects of information, emotion, aesthetics, and social presence. We found that consumers prefer product photos with a larger key object, lower entropy on key objects, a warmer color, a higher contrast, a higher depth-of-field, and more social presences. This research introduces a Big Data-based approach to study the impact of e-commerce systems' visual features on consumers.

Keywords: Image-processing, E-commerce, Consumer purchase, Big data.

1 INTRODUCTION

Determinants of consumer's purchase decisions are of long-term interest to researchers (Lichtenstein et al., 1993; Olshavsky, 1985) and practitioners. Previous research has identified several factors, such as product brand (Fournier, 1998), quality (Olshavsky, 1985), functionality, and price (Degeratu et al., 2000). Furthermore, the impact of online word-of-mouth on sales has received much attention from researchers (Chevalier & Mayzlin, 2006; Zhang et al., 2012). In this e-commerce era, the intangible online shopping environment (Laroche et al., 2005) brings extra challenges. This research is specifically interested in the impact of products' visual presentation on online shopping.

In an offline context, product visual presentation is affected by product design (Creusen et al., 2010; Hollins & Pugh, 1990), store decoration, and product arrangements (Vieira, 2010). In an online context, the store "decoration", i.e., Website design, has been widely studied in HCI literature (Karimov et al., 2011; Lohse & Spiller, 1998). It is found that Website quality, including perceived visual appeal, influenced perceptions of product quality and purchase intentions (Wells et al., 2011). Product photos are another dimension affecting product visual presentation.

Product photos are one major channel for online consumers to understand a product's design and quality. Chau et al. (2000) compared the use of pictures and text in presenting products and found that when purchasing familiar products, pictures exceed text in both efficiency and effectiveness. Song and Kim (2012) studied the impact of picture size on purchase intention. They argued that larger pictures could help customers receive more information and increase purchase intention. Hassanein and Head (2007) explored the case where text and pictures representing social presence are associated with product photos and found that would increase consumers' enjoyment and trust towards online shopping. There were also studies investigating the use of animation/interactive techniques in presenting products. Hong et al. (2004) found that applying flash highlights on product information does attract users' attention but may not increase recall of the item. Jiang and Benbasat (2007) found that the use of videos or virtual interactive presentations improved the perceived helpfulness of the Website for understanding products and improved the actual received product knowledge under moderate task complexity. Park et al. (2008) found that the rotation of products in a 3-D presentation affected consumers' perceived information, mood, attitude, and purchase intention.

Most previous studies on product photos took an experiment-based approach, which delivered strict theory testing but only covered a small range of photo characteristics. Recently, computer scientists have put significant efforts on automatic image-processing (Nixon & Aguado, 2012) and developed high-dimensional features to understand the semantics of images. Our research employs these advances to measure the impact of product photos on online consumers' purchase intention. We are able to conduct a large scale empirical study and have strict validation of photos' impact.

People's online shopping behavior is affected by many confounding factors. To rule them out to a maximum extent, we conduct this study in a social shopping context. Social shopping Websites allow people to share products they found on e-commerce Websites. They often have a simple interface mainly showing product photos. Such an interface allows consumers to focus on product photos and allows us to gauge products' visual presentation effect.

In this research, based on literature in HCI and psychology, we focus on four types of visual stimuli in product photos: information, emotion, aesthetics, and social presence. We collected a dataset from the largest social shopping Website in China, Mogujie.com, and conducted an empirical study to examine such features. It is found that these aspects of photos do affect consumers' online purchase intentions.

This research joins two types of techniques: (1) image-processing to handle the large volume of image data; and (2) econometrics analysis to establish causal relationships. Advances in high-throughput image-processing techniques make it possible to use large volumes of heterogeneous data to conduct large-scale empirical studies in this Big Data era. Theoretically, the research relates theories on human behavior with measurements developed in computer science to study product photos' impact on human perceptions. Practically, it generates guidelines for e-commerce retailers on how to prepare their product photos to increase sales.

2 THEORETICAL FRAMEWORK AND RELATED LITERATURE

Based on previous literature, we explore four aspects of product photos to assess their impacts on consumer purchase intent: information, emotion, aesthetics, and social presence. Particularly our study assumes a reasonable good quality of the products, i.e., the product photo plays a role of convincing the product is worthwhile to buy and there is no concern of cheating.

2.1 Information Embedded in Product Photos

In an offline shopping environment, consumers usually have direct access to products and can inspect the product to make purchase decisions. In the intangible online shopping process (Laroche et al., 2005), consumers need to get product information to reduce their decision-making uncertainty. Product photo is one major channel for consumers to understand the features of the product. Similar as advertising (Shavitt et al., 1998), product photos reduce consumers' uncertainty about the product. In advertising, the amount of information contained in advertisements is found to be a key issue influencing customers' decisions (Abernethy & Franke, 1996). In e-commerce context, Song and Kim (2012) employed the size of product photo as a measure of the photo's embedded information and found that information influences perceived risk and further influences patronage intent. It is found that more product information eases consumers' decision making and is positively correlated with purchase intention (Kim & Lennon, 2000). Particularly, on products with good qualities, a product photo with more details better shows the advantage of the product to consumers and thus increase the customer's intention to purchase. We conjecture:

H1: On products with reasonably good qualities, the amount of information embedded in product photos will be positively related to online consumers' purchase intent.

2.2 Emotion Implied by Product Photos

In addition to deliver product information, product photos also convey emotional messages to consumers. In marketing research, emotion is considered as one of the five major consumption values (functional value, conditional value, social value, emotional value, and epistemic value) to explain consumers' shopping behavior (Sheth et al., 1991). Westbrook and Oliver (1991) studied the relationship between emotion and consumer satisfaction. Holbrook and O'Shaughnessy (2006) argued the important role of emotion in advertising. In general, a positive emotion with comfortable and cheerful feelings makes the consumers happier and increases their intention to purchase.

In the context of e-commerce the emotion delivered through product photos may also influence consumers' purchase decisions. In psychology, it is recognized that different colors lead to different emotional perceptions (Hemphill, 1996; Joshi et al., 2011). For example, red has been associated with excitement, orange has been associated with distress and upset, and blue is associated with comfort and security (Wexner, 1954). In a simplified dimension, colors can be classified to cool colors (green, cyan, blue) and warm colors (red, orange, yellow), where warm colors are physically arousing and exciting and are often associate with positive emotions (Lavie et al., 2011; Terwogt & Hoeksma, 1995). In previous research on physical store design, stores with warm colors are found to attract more consumers (Bellizzi et al., 1983). Extending previous theoretical work to products in an e-commerce context, we argue, given a same online store decoration, product photos deliver more positive emotional messages tend to attract more consumers. By operationalize the emotional implications using colors of products, we conjecture that:

H2: On products with reasonably good qualities, the ratio of cool colors of product photos will be negatively related to online consumers' purchase intent.

2.3 Visual Aesthetics of Product Photos

Visual aesthetics refers to the aesthetic properties of a product photo. Researchers have been increasingly exploring the impact of aesthetic aspects on users in HCI research. Aesthetics was found to be a strong determinant of pleasure experienced by users when interacting with a computer (Jordan,

1998). In the history of World Wide Web and e-commerce, the visual aesthetics of Webpages have always been pursued by practitioners. Schenkman and Jönsson (2000) studied the relationship between aesthetics and preferences for Webpages, and found that beauty was considered to be a primary predictor of general impression and preference of Website. Noting visual aesthetics' influence on user satisfaction, Lavie and Tractinsky (2004) developed a measurement of perceived Website aesthetics, including classic aesthetics and expressive aesthetics. Moshagen and Thielsch (2010) further investigated the visual aesthetics of Websites and identified four facets of aesthetics: simplicity, diversity, colorfulness, and craftsmanship.

From the perspective of product design, visual aesthetics is also an important factor. Creusen et al. (2010) assessed consumers' preference for products' visual complexity and symmetry based on the importance of product value. Consumer's perception of products can also be influenced by the aesthetics of the context the products are presented. Wells et al. (2011) found that Website quality, including perceived visual appeal, influenced perceptions of product quality and purchase intentions. In an e-commerce Website, product presentation is jointly determined by Website design, product photo, and product design. Thus, after controlling the effect of Website design, we conjecture that:

> *H3: On products with reasonably good qualities, the aesthetics of product photos will be positively related to online consumers' purchase intent.*

Assessing photo aesthetics is complicated and still being investigated in image-processing (Dhar et al., 2011; Marchesotti et al., 2011; Wu et al., 2011). This research does not intend to pursue such a machine learning direction. Instead, we choose to employ well-established rules to gauge photo aesthetics.

2.4   Social Presence in Product Photos

Social presence is a widely recognized factor that influences consumer behavior in marketing. Social presence refers to the extent to which a medium allows users to experience others as being psychologically present (Fulk et al., 1987). Compared with off-line business, e-commerce is usually being considered as lacking human warmth and sociability (Gefen & Detmar, 2003), since it is more impersonal, anonymous and automated (Van der Heijden et al., 2003). One approach to address this limitation is to include photos and messages signalling human's involvement with a product. For example, the use of human models has been found to affect advertisement outcomes (Buunk & Dijkstra, 2011) and is being widely adopted in practice. In e-commerce, Cyr et al. (2009) found that the appearance of human images on Webpages improves image appeal and perceived social presence, which makes the Website more trustworthy. Hassanein and Head (2007) explored the case where text and pictures representing social presence are associated with product photos on e-commerce Websites and found that would increase consumers' enjoyment and trust towards online shopping. In this research, we focus on human models as a reflection of social presence in product photos. Given that products on e-commerce Websites may have different vendors and sellers, we argue the use of human models and other social presence signals may increase customers' feeling on each of the product and further affect consumers' purchase intents on each of the products. By applying image-processing techniques, we are able to identify humans from product photos and gauge their impact. We conjecture that:

> *H4: On products with reasonably good qualities, the appearance of humans in product photos will be positively related to online consumers' purchase intent.*

3   MOGUJIE: A SOCIAL SHOPPING TESTBED

Mogujie.com is a social shopping Website where users share products they found on Taobao.com. Founded in 2011, Mogujie is now the largest social shopping Website in China, with more than 20 million registered users. Targeting young female users, the Website mainly focuses on sharing information on clothes, shoes, bags, accessories, household goods, cosmetics, and so forth. Due to the self-selection effect of the Website, products shared on Moguojie generally have a reasonably good

quality, i.e., the shared products often have fashion designs and beautiful colors. Upon on these reasonably good products, product photos further help and affect consumers' purchase decisions.

Figure 1.   Screenshot of Mogujie.com

Mogujie provides a very simple interface and use case for users. Figure 1 shows a screenshot of Mogujie.com. If a user found an interesting product on Taobao, she can create a Webpage for the product by providing the Taobao link and a couple of product photos (most users only choose one photo). The main product photo selected by the sharing user is usually in high-resolution and put on the left side of the Webpage. The right side of the interface shows the product name and price, which are retrieved from Taobao. If follow-up users found other Taobao sellers selling the product, they can provide the links, and information from the different sellers will be shown together (so that a user can follow the Taobao links to make a purchase). It should be noted that while Mogujie allows multiple sellers for a product on a product page, there still exist products with multiple Webpages since the original sharing user may not intensively search the Website to avoid duplications. Below the Taobao information region, the number of "likes" received from other users is shown. Given the nature of the Website, the number of "likes" represents the number of consumers interested in buying the product. Since the interface is uniform on Mogujie, its impact on consumer purchase intention (i.e., likes) is uniform across products. Due to the simple layout, users' decisions are mainly based on the products' photos.
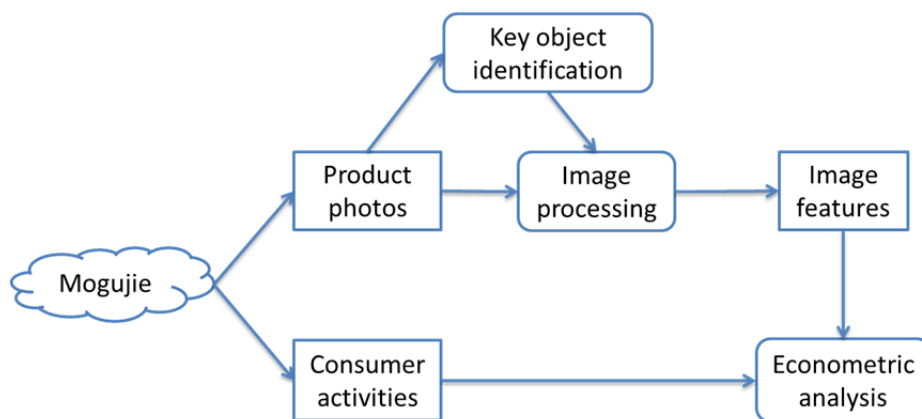
4   METHODOLOGY

Figure 2.   Research procedure

Figure 2 shows the generic process of this research. After collecting data on user activities and product photos from Mogujie.com, we apply image-processing techniques to generate image features for the hypotheses we proposed in Section 2. Since the purpose of product photos is to present the products, which are often the key objects in photos, we also examine the image features on the regions of key objects identified from product photos, when applicable. Then we conduct an econometric model to establish the causal relationship. The purpose of the framework is to establish causal relationship between features of product photos (measured by image-processing techniques) and customers' responses to the product photos in purchase intents.

4.1 Variables

Dependent variable: We choose the number of likes for each product on Mogujie as the indicator of the number of consumers who have an intention to purchase. The users of Mogujie are clear about the marketing nature of social shopping Websites. Users' "like" actions generally reflect their judgment on whether the product is worth buying.

Control variables: Following classic marketing literature, we control the effect of price. Considering that the products appear on different Mogujie pages, which take different efforts to find, we control the page of the product in this research. We also control the total number of likes shown on the Webpage which may influence consumers' decisions. We control the height and width of photos, which have only slight differences across products on Mogujie. We also control seasonal effects through the setup of our econometric model.

Independent variables: Aligning with our hypotheses, we apply image-processing techniques on product photos collected from Mogujie and derive independent variables. In the following subsections, we elaborate how they are selected and calculated.

In image-processing, a computer image is often presented as a matrix of pixels. Each pixel has three values representing the three dimensions in a color space. Two widely used color spaces are the RGB space and HSL space. The three dimensions in the RGB space represent red, green, or blue, which can be mixed to derive other colors. HSL space is a transformation of RGB space containing dimensions of hue, saturation, and lightness.

4.1.1 Information Embedded in Product Photo

To gauge the amount of information embedded in the image, we employ two types of measures, size related measures and entropy related measures.

Since the photos on Moguojie are generally in the same size, we focus on relative size of the product on the product photo. Here, we employ the saliency region method (Hou & Zhang, 2007) to identify the key objects in photos (as shown in the first two images of Figure 3). Assuming the identified key objects of a product photo is the product for sale, we measure the relative size (i.e., width ratio to the photo and height ratio to the photo) of the product region. This tells us how large the product appears in the photo, indicating the amount of information about the product people receive from reading the photo. Since the purpose of product photos is to present product, these measures fit our purpose to examine information's effect.

Furthermore, we employ the entropy measure in information theory to measure uncertainty of product photos. In image-processing, to calculate entropy, the order of the pixels is ignored and only the distribution P of the RGB values of the pixels are used. entropy is calculated as:

$$E = -\sum (P * \log_2(P)).$$ (1)

Here, a color image is often converted to a grey-scale image by averaging the RGB values. We apply this measure on both the entire image and the key object region to reflect the amount of product information embedded in the product photo and the product area of the photo. In information theory, statistical entropy is a probabilistic measure of uncertainty or ignorance; information is a measure of a reduction in that uncertainty. Thus information and entropy has a negative correlation. Large entropy images are relatively random and more difficult to compress and to digest by humans.

Figure 3.   Saliency region for key object identification and measuring the fitness of rule-of-thirds

4.1.2   Emotion Implied by Product Photo.

To gauge the emotional effect of images, we focus on the cool vs. warm color of images. The cool vs. warm color is differentiated using the hue in HSL color space. As shown in Figure 4(b), hue varies from 0° to 360°, which iteratively goes through red, orange, yellow, green, cyan, blue, purple, and other intermediate colors. Obviously, hue is not a linear measure. In this research, we convert it to a binary value where colors with a hue value between 90° and 270° are annotated as cool colors (Caponigro, 2011). Since hue is defined on each pixel, we build a variable on the percentage of cool color pixels to measure the relative coolness or warmness of the product photo.

In this dimension, we do not measure the color of product regions, since we control the product characteristics, including product color, in the econometric model.
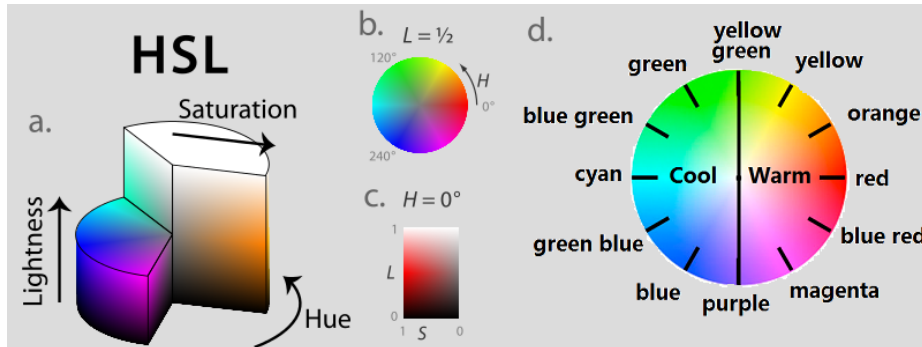

Figure 4.   HSL Color Space: (a) A cut-away 3D representation. (b) Plot of hue and saturation under constant lightness. (c) Plot of lightness and saturation under constant hue. (d) Colors according to hue value. (http://en.wikipedia.org/wiki/HSL_and_HSV)

4.1.3   Visual Aesthetics of Product Photos

To gauge aesthetics of images is complicated. In this paper, we employ three types of basic measures, which are related to color, depth of field, and rule-of-thirds, instead of complicated machine learning algorithms to achieve this goal.

We employ three classic measures to assess color-related aesthetics: saturation, lightness, and contrast. Saturation and lightness are two dimensions of the HSL space that capture colorfulness and brightness respectively. By increasing saturation, one can increase the separation between colors. In general, high saturated color is considered more natural. The lightness reflects how dark a person would perceive a color. Since both saturation and lightness are pixel level measures, in this research, we average the two measures across pixels to get the measures of the entire photo. Contrast is the separation between the dark and bright areas of the image, which can be calculated as:

$$\text{Contrast} = std\left(\frac{L - \min(L)}{\max(L) - \min(L)}\right), \tag{2}$$

where L represents the matrix for lightness in the HSL color space. By increasing contrast, one can increase the separation between dark and bright, making shadows darker and highlights brighter. Note that the relationship between these three color-related measures and visual aesthetics may be complicated and nonlinear. In this research we simplify the investigation on these aspects and hypothesize that a more beautiful picture has relatively higher saturation, lightness, and contrast (Labrecque & Milne, 2011) if the product photo is reasonably good, such as in Moguojie.

Depth of field (DoF) is a photography concept. An image displaying a low DoF can emphasize an object of interest by capturing it in sharp focus, while leaving objects at other depths blurred. In order to measure whether a photo is in a low DoF, we employ the model of Dhar et al. (2011), which extracts Daubechines wavelet-based features and builds an SVM classifier based on 2,000 manually labeled images, to judge whether our photo is in a low DoF.

Rule-of-thirds (RoT) is a well-known composition principle in photography, which means the major subject of an image should be put at about the one-third position of the photo (Boselie, 1984). In order to measure the fitness of RoT, we first identify the figure's key objects. Then, we measure the smallest distance (as the percentage of photo width or height) from the centroid of the object to the vertical and horizontal lines (as shown in Figure 3). A smaller value indicates a better fit.

For the aesthetics measures, we can also measure the saturation, lightness, and contrast on the key objects' area. But DoF and RoT are not applicable on the key objects, due to their global nature.

4.1.4 Social Presence in Product Photos

In this research, we account human models as an indicator of social presentments. In image-processing, face detection technologies (Ramanan, 2012) are unique categories that can be used to identify human models in photos. In this research, we employ the method and program developed by Nilsson et al. (2007) to detect faces on product photos. We then count the number of human faces as the measurement of social presence. A large number of faces shows a stronger sense of social presence. Such as technique may not be able to capture the products with models whose faces are not shown. However, we consider human models showing face on product photos deliver more sense on social presence. Note that this measure cannot be applied on key objects of the photo either.

Table 1 summarizes the measures we derived on the four dimensions, including both photo-level measures and object-level measures (when applicable).

Type	Variable	Explanation
Information	*ObjectWidthRatio*	Object width/photo width
	ObjectHeightRatio	Object height/photo height
	Entropy	The entropy for the product photo
	ObjectEntropy	The entropy for the object
Emotion	*CoolColorRatio*	Percentage of pixels with a cool color
Aesthetics	*Saturation*	Average saturation of product photo
	ObjectSaturation	Average saturation of the object
	Lightness	Average lightness of product photo
	ObjectLightness	Average lightness of the object
	Contrast	Contrast of product photo
	ObjectContrast	Contrast of the object
	LowDoF	Whether a product photo has a low depth of field
	VerticalRoT	Normalized distance to the closest vertical trisection line
	HorizontalRoT	Normalized distance to the closest horizontal trisection line
Social Presence	*NumHumanFace*	Number of human faces on the product photo

Table 1:   Overview of independent variables

4.2 Econometric Model

We collect a panel data to capture the change of likes across time. Noting that one product may be posted on Mogujie multiple times with different photos, we take a first difference approach on photos of same products to rule out the impact of product characteristics.

Figure 5.   Examples of matched photos on identical products

We hired a research assistant to manually code the identified pairs for possible matched products. Photos within the same product category are packaged into one folder to ease difficulty for identifying pairs. Figure 5 shows some examples of matched photos. The difference between photos can be in the product position, background, or human models.

Assuming we have a product i with two photos A and B, each follows a simple linear model:

$$Likes_{i,t}^{A;B} = \alpha + \beta_1 CLikes_{i,t-1}^{A;B} + \beta_2 \text{Price}_{i,t-1}^{A;B} + \beta_3 Page_{i,t-1}^{A;B}$$
$$+ \text{ImageFactors}_i^{A;B}\Gamma + \text{ProductFactors}_{i,t-1}\Lambda + \varphi_i + \theta_t + \varepsilon_{i,t}^{A;B} \text{,}$$

(3)

where we use superscript $A;B$ to represent each photo. $Likes^{A;B}_{i,t}$ is the number of likes in period t. α contains the Website-level time-invariant effect. $CLikes^{A;B}_{i,t-1}$ controls the herding effect caused by the cumulative number of "*Likes*" showing on the Webpage. $Price^{A;B}_{i,t-1}$ are control variables that may vary by time and product. $Page^{A;B}_{i,t-1}$ are control variables for which page the product is showing on, which may vary by time and product. $ImageFactors^{A;B}_{i-1}$ are the independent variables developed from the product photo, which is time-invariant for each photo but may be different across photos. $ProductFactors_{i,t-1}$ are product characteristics, such as brand, quality, advertisements, etc., which are the same for photos A and B. φ_i is the product-level fixed effect. θ_t is the time-variant fixed effect of the entire Website, such as the change of user base caused by promotions. $\varepsilon^{A;B}_{i,t}$ is the random noise. After conducting one difference on paired photos A and B, we can get a model:

$$\Delta Likes_{i,t} = Likes_{i,t}^A - Likes_{i,t}^B$$
$$= \beta_1 \Delta CLikes_{i,t-1} + \beta_2 \Delta \text{Price}_{i,t-1} + \beta_3 \Delta Page_{i,t-1} + \Delta \text{ImageFactors}_i \Gamma + \varepsilon_{i,t} \text{.}$$

(4)

By conducting the first difference, the product-related factors and seasonal effects are cancelled out. We can establish the causal relationship between *ImageFactors* and *Likes*, which represents purchase intention. Furthermore, considering that cumulative likes, prices, and page do not follow a normal distribution, we create an alternative model by applying log transformation on the three variables:

$$\Delta Likes_{i,t} = \beta_1 \Delta Log(CLikes_{i,t-1}) + \beta_2 \Delta Log(\text{Price}_{i,t-1})$$
$$+ \beta_3 \Delta Log(Page_{i,t-1}) + \Delta \text{ImageFactors}_i \Gamma + \varepsilon_{i,t} \text{.}$$

(5)

Since the image features are all derived from the image pixels' values, by nature, there is a high correlation between each other. Thus, we employ the Ridge regression to estimate coefficients of the model. We used the ridge package in R to implement this regression. The package automatically chooses the parameters based on (Cule & De Iorio, 2012).

5 RESULTS AND DISCUSSION

5.1 Dataset

Variable	N	Photo A in the Pair					Photo B in the pair			
		Mean	SD	Min	Max		Mean	SD	Min	Max
CLikes	310	641.11	1770.7	1	13434		815.69	2282.02	2	15010
Price	310	158.35	133.28	13.9	1080		155.63	143.29	10	1588
Page	310	25.01	26.12	1	137		23.95	26.35	1	137
Height	310	296.42	42.33	143	360		297.33	41.96	133	377
Width	310	224.93	1.03	207	225		224.96	0.63	214	225
ObjectWidthRatio	310	0.75	0.15	0.2	1		0.76	0.15	0.1	1
ObjectHeightRatio	310	0.75	0.16	0.14	1		0.75	0.16	0.2	1
Entropy	310	6.93	0.79	2.99	7.91		6.88	0.85	2.82	7.9
ObjectEntropy	310	7.34	0.49	3.72	7.95		7.32	0.52	3.73	7.96
CoolColorRatio	310	0.23	0.22	0	0.94		0.22	0.21	0	0.96
Saturation	310	0.34	0.14	0.05	0.8		0.36	0.15	0.04	0.83
ObjectSaturation	310	0.36	0.15	0.07	0.88		0.38	0.16	0.04	0.8
Lightness	310	0.66	0.13	0.36	0.92		0.67	0.12	0.35	0.93
ObjectLightness	310	0.59	0.13	0.26	0.92		0.6	0.13	0.2	0.88
Contrast	310	0.25	0.07	0.07	0.42		0.25	0.07	0.1	0.41
ObjectContrast	310	0.25	0.07	0.08	0.43		0.25	0.07	0.1	0.42
LowDoF	310	0.67	0.47	0	1		0.70	0.46	0	1
VerticalRoT	310	0.13	0.04	0.01	0.18		0.14	0.03	0.01	0.29
HorizontalRoT	310	0.12	0.04	0	0.26		0.12	0.04	0	0.2
NumHumanFace	310	0.27	0.52	0	2		0.22	0.49	0	2

Table 2:   Descriptive statistics of the data in the last week (No. of Obs.=310)

In this research, we collect panel data from December 9, 2013 to February 10, 2014 through Web crawling every week. We collected all photos from Mogujie in two categories: clothes and shoes. The clothes category has around 20K products and the shoe category has around 14K products. We hired a research assistant to code the images and find 1,010 photos that can be matched to 931 pairs, including 470 pairs of clothes photos and 461 pairs of shoes photos. (One product may have more than two Webpages and thus generate more than one matched pair. We account all combinations of the photos of a same product to generate the matched pairs and each pair is a record in our econometric model, i.e., *i*.) In order to control confounding factors, we only keep the products with one seller and the photo pairs with posting dates that are within two weeks' range. Eventually, we identify 310 photo pairs. Due to new products being added to the Website, the earlier batches contain less photo pairs. For example, the first week contains 259 photo pairs.

Table 3 reports the descriptive statistics of the dataset on the last week. On average, each photo receives about 600~800 likes from the posting day to February 10, 2014. The average price of the products is 140~160 RMB. On average the photos are put on 24~25 pages on the product list. Almost all photos' widths are 225, while their heights vary. On average the entropy value is around 7. The key objects often occupy about ¾ of the area on photos. On average about 22%~23% of the image

colors are cool colors. The average saturation is about 0.35. The average lightness is about 0.66. The average contrast is about 0.25. About 67%~70% of the photos are in low DoF. Distances to trisection lines are about 12% ~14% of the photo width or height. On average, about ¼ of the photos have human models.

5.2 Results

	Model (1)			Model (2)		
	Coefficients	p value		Coefficients	p value	
$\Delta LogCLikes_{t-1}$				0.278	0.014 **	
$\Delta CLikes_{t-1}$	0.000	0.269				
$\Delta LogPrice_{t-1}$				0.001	0.752	
$\Delta Price_{t-1}$	0.000	0.495				
$\Delta LogPage_{t-1}$				0.215	0.421	
$\Delta Page_{t-1}$	0.006	0.091 *				
$\Delta Height$	-0.001	0.378		-0.004	0.485	
$\Delta Width$	0.002	0.961		-0.012	0.948	
$\Delta ObjectWidthRatio$	0.110	0.718		0.175	0.890	
$\Delta ObjectHeightRatio$	0.611	0.046 **		2.850	0.024 **	H1
$\Delta Entropy$	-0.131	0.044 **		-0.238	0.439	
$\Delta ObjectEntropy$	-0.326	0.003 ***		-1.251	0.012 **	
$\Delta CoolColorRatio$	-0.936	0.000 ***		-3.357	0.001 ***	H2
$\Delta Saturation$	0.158	0.668		-0.551	0.731	
$\Delta ObjectSaturation$	0.304	0.372		1.166	0.432	
$\Delta Lightness$	-0.167	0.681		0.468	0.812	
$\Delta ObjectLightness$	-0.461	0.288		-1.638	0.423	
$\Delta Contrast$	2.649	0.001 ***		8.510	0.024 **	H3
$\Delta ObjectContrast$	1.977	0.015 **		3.302	0.357	
$\Delta LowDoF$	-0.228	0.059 *		-0.942	0.041 **	
$\Delta VerticalRoT$	1.319	0.322		-0.422	0.936	
$\Delta HorizontalRoT$	0.350	0.762		-1.169	0.789	
$\Delta NumHumanFace$	0.411	0.000 ***		1.600	0.000 ***	H4

Table 3. Regression results (* p<0.1, ** p<0.05, *** p<0.01)

Table 3 shows the regression results of the two models shown in formulas (4) and (5). In general the results on the independent variables are pretty consistent.

For the information-related measures, it is found that a relatively larger object lead to a higher number of likes. Showing a large product on the photo makes it easier for the customers to inspect the product. Given that the product is in reasonably good quality, providing more information makes it easier for the customer to appreciate the product and decide to buy. For the entropy measure, there is a significant negative relationship between photo-level (in model 1) and key object-level (in both models) entropy and the number of likes from consumers. Since information reflects the reduction of entropy/uncertainty, the negative coefficient shows that consumers prefer the object to be less random, more information, and more organized. From these two types of measures, it is shown that product information delivered through product photos affect consumer's purchase intention. Photos with more and better organized information tend to attract customers in the setting of our dataset (with reasonably good quality products). Hypothesis 1 is partially supported.

For the emotion's perspective, the coefficient on the variable of cool color shows that a photo with more cool color pixels has a lower number of likes. It indicates that the positive emotion delivered by

warm colors may affect the consumers, change their mood of purchase, and increase the purchase intent. Hypothesis 2 is supported. (Since previous research also use individual colors to capture the different types of emotional message, we further experimented with variables build up on each color. The results are consistent that certain colors representing positive and happy emotions lead to more likes of the consumers.)

Among the aesthetics measures, it is found that high contrast leads to more likes (in both models), and a high contrast of objects (in model 1) further leads to more likes. A low DoF leads to a low number of likes, which shows that in the e-commerce setting consumers prefer photos that are sharp in all places, which helps them identify product details. Hypothesis 3 is partially supported. The other measures, saturation, lightness, and the two RoT measure, are not significant in the regression, which may due to the nonlinearity and interactions among these factors. It is necessary to develop more comprehensive models and measures to assess photo visual aesthetics in future research.

Finally, we employ the number of human faces on a product photo to represent the social presence signals to consumers. It is found that this variable is significantly correlated with number of likes received. A product photo with more clues of social presence may have increased consumers trust on the product and increases consumers' purchase intents. Hypothesis 4 is supported.

In general, we can see that consumers prefer product photos with a larger key object, lower entropy on key objects, a warmer color, a higher contrast, a higher depth-of-field, and more social presences. The coefficients of the control variable indicate that the cumulative sales showing on Webpage and the rank of page on which the product shown (i.e., the number of clicks/efforts needed to find the product on product list pages) may affect consumers' purchase intention. Price is not shown significant in this research. We project this may due to the nature of the "like" action in Mogujie. At the stage of clicking "like," the customers show an interest to the product but do not need to commit purchase. Thus, they do not need to consider the price of the product. To fully investigate the interaction between price and other image factors on customer purchase, it will be necessary to employ sales data.

6   CONCLUSIONS AND FUTURE WORK

In this research, we studied how the visual clues delivered though product photos can be captured with the help of modern image-processing techniques and affect consumer preferences in a social shopping context. We design variables capturing the visual clues related to information, emotion, aesthetics, and social presence in photos. We apply image-processing techniques to quantify those variables and conduct an empirical study on a data set collected from one of the largest social shopping Websites in China. The results show that product visual presentation does influence consumer purchase intention. In general, consumers prefer product photos with a larger key object, lower entropy on key objects, a warmer color, a higher contrast, a higher depth-of-field, and more social presences. Such findings can be used in practice to direct the product presentations in e-commerce Websites. Furthermore, the paper draws attention to using image-processing techniques to study human behavior through large-scale empirical studies.

In the future, we will improve the econometric model. We will also develop other measures on visual information under the direction of behavioral theories. Our ultimate goal is to develop a framework that makes use of image-processing techniques to discover visual features' effect on consumer's behavior, which can also be used by e-commerce stores to improve sales.

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