

# The Impact of Photo Aesthetics on Online Consumer Shopping Behavior: An Image-Processing-Enabled Empirical Study

*Research-in-Progress*

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## Abstract

*Determinants of consumer's shopping behavior are of long-term interest to researchers. 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 shopping behavior. 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 use a real company dataset from a social shopping Website, which has a simple interface allowing consumers to judge products mainly based on their photos. We employ two-stage nested logit model embedded with differences-in-differences approach and examine product photo characteristics from the aspects of color, composition, complexity, and model face. We found that consumers prefer to click product photos with a warmer color, a larger key object, appropriate complexity.*

**Keywords:** Image-processing, visual aesthetics, nested logit model, big data

## Introduction

E-commerce marketplaces have grown at a large scale along with the rapid development of the Internet. Users enjoy the convenience and low prices provided by online shopping. The intangible online shopping environment (Laroche et al. 2005) introduces extra challenges in this e-commerce era. Without physical items to touch and feel, users browse the provided product descriptions and photos and then decide which ones to click in the details page (Goswami et al. 2011). Therefore, effective communication between shopper and e-retailer is becoming very important. However, textual information such as title and description can only provide users limited imagination within the scope of language (Di et al. 2014; Muter and Mayson 1986). The product photo is a major channel for online consumers to understand the design and quality of a product. Park et al. (2005) research showed that the inclusion of an image helps reduce the perceived risk for users. A photo can provide a unique yet profound channel to convey to users visual information that cannot be communicated through text (Pellegrino et al. 1977). In this research, we focus on one of the few aspects a retailer can manipulate in e-commerce marketplaces, namely, product photos, and investigate which aspects of product photos can increase consumer clicks.

In practice, e-retailers have noted the importance of photos and have adopted various visualization tools to improve the effectiveness of product presentation, such as using zoom and panning functions (Yoo and

Kim 2012). The more appealing the product display, the higher the number of clicks it will receive (Then and DeLong 1999). This issue also attracts attention in the academe. For example, Hong et al. (2004) found that applying flash highlights on product information does attract users' attention but may not increase item recall. Park et al. (2008) found that the rotation of products in a 3D presentation affects the perceived information, mood, attitude, and purchase intention of consumers. People make judgments and decisions based on internal aesthetic responses to aspects of the world (Palmer et al. 2013). Wang et al. (2011) found that aesthetic formality and appeal influences the perceived service quality, satisfaction, and arousal of consumers, and further affected their purchasing behavior. Noticing the importance of visual aesthetics, we rely on aesthetical theories from psychology and their applications in HCI to identify photo aesthetics.

Most previous studies on product photos utilized an experiment-based approach, which delivered strict theory testing but only covered a small range of photo characteristics. Currently, computer scientists are devoting significant efforts into automatic image-processing (Nixon and Aguado 2012) and have developed high-dimensional features to understand the semantics of images (Barnard and Forsyth 2001). Thus, unlike previous experimental studies, our research employs image-processing technology to measure the impact of product photos on the shopping behavior of online consumers. We conduct an empirical research to study the impact of product photo characteristics on consumer shopping behavior in an e-commerce environment. We propose a conceptual framework and hypothesize that photo-specific characteristics affect users' shopping behavior. We employ a two-stage nested logit model embedded with a differences-in-differences (DID) method to rule out unobservable factors that are influential to users' shopping behavior, such as style, popularity, and brand name.

## **Literature Review**

### ***Visual Presentations on the Web***

Considering the intangibility of online shopping, consumers want to obtain more information to insure their shopping quality. The importance of images and product photos has long attracted researchers (Scott 1994). The product photo itself provides visual or tangible cues for consumers to understand products (Laroche et al. 2005). Prior research has shown the great importance of employing product photos for users in an e-commerce market. Bland et al. (2007) research showed that product pictures are influential factors for risk-reduction in eBay auctions. Lewis (2011) investigated the effects of the number of photos embedded in item descriptions on demand in eBay motors and concluded that more photos helped enhance selling, especially for old cars. Clear and detailed product photos were also shown to be helpful in reducing the perceived risk for online purchasing (Koehn 2003; Wolfenbarger and Gilly 2001).

Aside from studies focusing on the impact of including photos, other papers studied user preference for the content of photos from the psychological perspective. Yoo and Kim (2012) examined how product coordination and a model's face affect consumer responses as measured by affective states, perceived amount of information, and purchase intention. Kim and Lennon (2010) investigated the effects of using a human model, color swapping, and enlargement on the consumers' emotional responses, which may consequently influence their cognitive and behavioral responses. These studies typically used experimental methods and obtained exciting results, and paved the way for future studies on online product presentation. However, they are limited to small user groups with subjective ratings and a lack of completeness and representativeness of the vast online users in a real market. To the best of our knowledge, quantitative studies on the impact of product photos are still limited and preliminary. Therefore, unlike previous studies, we utilize an advanced vision technique to quantize the attractiveness of product photos of clothes and shoes, i.e., the ability to draw consumers' attention and clicks.

### ***Theories of Visual Aesthetics and Its Applications***

The American Heritage Dictionary of English Language defines aesthetics as, "a conception of what is artistically valid or beautiful." Aesthetics is also regarded as "the philosophy of beauty" in the literature of arts (Dickie 1997). It is also connected with affect/mood, emotion, and feeling (Norman 2007). This emotional connection makes aesthetic concerns highly important and builds the bridge between a product and a user's feelings (David and Glore 2010). Aesthetics was found to be a strong determinant of pleasure experienced by users when interacting with a computer (Jordan 1998).

Prior research has recognized the importance of creating an aesthetic website in enhancing customers' online experience (Wang et al. 2011). Tuch et al. (2009) investigated the effects of the visual complexity of websites on the experience, physiology, performance, and memory of users. Cyr et al. (2010) studied the effects of color appeal on websites. Wu et al. (2011) estimated the visual quality of Webpages by using aesthetic elements, such as layout, visual complexity, and colorfulness. Altaboli and Lin (2011) investigated the effects of layout elements on screen design aesthetics. Reinecke et al. (2013) quantified visual complexity and colorfulness and predicted users' first impressions of website aesthetics. Palmer et al. (2008) explored viewers' aesthetic preferences for the position (including rule of thirds) and direction of objects within pictures. Buunk and Dijkstra (2011) showed that women pay more attention to a product if it is promoted by an attractive model.

## **Research Framework**

We identify four promising factors for photo aesthetics, namely, color, spatial composition, complexity, and model face, based on the review of related literature in Section 2.2 (Bauerly and Liu 2006; Cyr et al. 2009; Moshagen and Thielsch 2010).

### **Color**

Extensive literature reveals that colors and their composition have a unique effect on aesthetic appraisal (Arnheim 1954; Kawabata and Zeki 2004; Martindale and Moore 1988; Solso 2003). Color has been recognized as a marketing tool to influence consumers' purchasing rates, time spent in the store (Bellizzi and Hite 1992), affective tone, arousal (Crowley 1993), and feeling (Kotler 1973). Extending previous theoretical work to products in an e-commerce context, we argue that given the same online store decoration, product photos that deliver more positive emotional messages attract more consumers. In the context of e-commerce, the emotion delivered through color may also influence the click behaviors of consumers. The effects of color on the design of websites in particular have likewise been demonstrated in HCI research (Cyr et al. 2010; Hall and Hanna 2004). Kotler (1973) indicated that atmospherics, such as colors, can help draw attention and create feelings that may increase purchasing intention. Lohtia et al. (2003) demonstrated that the number of colors can influence click-through rate in banner ads. We describe color for photos by using multiple measures, including lightness, saturation, the ratio of cool color and the ratio of clear color. Therefore, we hypothesize the following:

H1: Using color aesthetically for product photos results in high incremental clicks for detailed page view.

### **Composition**

Composition is an important aspect of photo aesthetics (Palmer et al. 2013). Photographers, painters, and other visual artists who work in 2D visual media continually face the problem of how to compose the subjects of their creations in aesthetically pleasing ways (Palmer et al. 2008). Photo composition refers to the placement of visual elements. Researchers have noticed the effects of spatial composition on creating aesthetical images and have investigated factors that influence humans' preference for spatial composition (Bauerly and Liu 2006; Palmer et al. 2008; Sammartino and Palmer 2012).

The size of a focal object is a compositional factor that influences aesthetic preference. Silvera et al. (2002) showed that people prefer large objects. Chandon et al. (2003) showed that larger ads resulted in a higher click rate compared to smaller ads. Thus, the size of major object is an aesthetical factor that should be considered. The location of object is another compositional factor that affects aesthetic preference. People prefer images that are more easily perceived (Winkielman et al. 2006). People are faster and more accurate at recognizing target objects in appropriate locations (Biederman et al. 1982). The well-known Rule of Thirds (RoT) is a popular composition rule used by photographers to create high-quality photos. The Rule states that dividing an image into horizontal and vertical thirds and placing the focal object around their intersections can help produce highly aesthetic photos. Thus, the location of the major object in a photo should be an aesthetical factor. We hypothesize the following:

H2: Arranging objects aesthetically for product photos results in high incremental clicks for detailed page view.

## **Complexity**

Complexity is widely identified as one facet of visual aesthetics in the realm of HCI and user interface design. Complexity refers to graphic diversity or richness (Kaplan and Kaplan 1982). As introduced by Leder et al. (2004) model, complexity plays a key role in the perception of visual stimuli. It has been shown to affect consumers' emotions and behavior (Deng 2010). Berlyne (1974) aesthetic theory predicts that stimuli with a moderate degree of complexity will be considered pleasant, whereas stimuli with either less or more complexity will be considered unpleasant.

Several empirical studies from the HCI field provide evidence for the influence of complexity on aesthetics. The complexity of a webpage background seems to affect the attitudes and intentions of users (Stevenson et al. 2000). Complexity has been demonstrated to be an important factor influencing users' first impression of a website (Tuch et al. 2012). Geissler et al. (2006) suggested that webpages with moderate complexity enhance the effectiveness of communication and lead to highly favorable consumer responses. Considering that users' responses for complexity are quite complex, we describe complexity for photos by using multiple measures, including degree of kurtosis, texture contrast, and number of key points. Thus, we hypothesize the following:

H3: Using complexity aesthetically for product photos results in high incremental clicks for detailed page view.

## **Model face**

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. Online shoppers prefer to see products displayed by human models instead of on mannequins (Kim et al. 2009). The presence of human models has been found to affect advertisement outcomes (Buunk and Dijkstra 2011) and has widely been adopted in practice. Especially for products without a strong brand image, a model's facial attractiveness is an important factor that affects user responses to the product (Joseph 1982). Given that products on e-commerce websites may have different vendors and sellers and may not have a strong brand image, we argue that the existence of a human face may increase users' feelings toward each product and further affect their click behavior on each product. By applying image-processing techniques, we can detect a human face from product photos and gauge their impact. We hypothesize the following:

H4: Using a model face properly for product photos results in high incremental clicks for detailed page view.

## **Empirical Model**

Users click a product for reasons other than the beauty of the product photo. Various other reasons may exist, such as the style of the product being popular or the brand of the product being attractive. Users can click one product because of its novel style or their affection for one brand. However, these factors are unobserved by researchers. Judging the degree of popularity of the style or the attractiveness of one product is difficult. The DID method has been widely adopted to solve this problem. Chevalier and Mayzlin (2006) explored the effects of book reviews on sales ranks on two websites with different dates, and used the DID approach to eliminate book- and site- specific effects. Zhu and Zhang (2010) studied the impact of online reviews on online game sales and employed the DID approach to eliminate unobserved common factors. In this research, we employ a two-stage nested logit demand model to study users' online click behavior toward different facets of photo aesthetics, especially when products are grouped into predetermined categories. Similar to Zhu and Zhang (2010) research, we utilize the DID approach in the nested logit demand model to avoid the effects induced by unobservable factors, such as popularity, brand, and quality. This DID approach enables us to test whether a relative increase in clicks for one product is a result of its different photos.

We assume that  $N$  products are available and an outside option is labeled as 0. Given that products are grouped into several categories, we place consider product category as a group, i.e., one nest exists for each product category. In the first stage, a consumer decides whether to click the detailed page of one product. In the second stage, if the consumer chooses to click the detailed page of one product, he or she then decides which product to click. The perceived utility of consumer  $i$  from viewing the detailed page of

one product  $j$ ,  $j \in [1, N]$  at time  $t$ ,  $u_{ijt}$  is affected by product price, the beauty of the photo, fashion style, perceived product quality, and other product characteristics. As clicking the detailed page for one product does not require paying for the product, price may not play that important role on the perceived utility. Thus, attractiveness, i.e., photo aesthetics, is the primary reason for a user to click on a product. Furthermore, the characteristics of product photo can reflect the product quality to a certain degree. Variables such as market share, prices, and product photo can be obtained directly from the original dataset. Measures for photo aesthetics can be computed from the product photo by employing image-processing technology. The consumer's utility,  $u_{ijt}$ , is expressed as a function of photo aesthetics, price, and other unobserved product characteristics.

$$u_{ijt} = X_j \beta_i + P_j \alpha_i + \xi_{jt} + \varepsilon_{ijt}, \quad (1)$$

Where  $X_j$  represents the measures of photo aesthetics for product  $j$ , a vector of observable characteristics of product  $j$ .  $\beta_i$  is a vector of coefficients (i.e., taste parameters) associated with those photo characteristics.

Note that  $P_j$  represents the price for product  $j$ , and  $\alpha_i$  is a scalar for a coefficient that captures the heterogeneous taste of customers toward product price.  $\xi_{jt}$  represents all unobserved characteristics to researchers of product  $j$  at time  $t$ .

Each customer  $i$  clicks the detailed page of a product that maximizes his/her utility. We denote the share of the potential market captured by product  $j$  in period  $t$  as  $s_{jt}$ . We use sub-category as a group and denote the share of product  $j$  within group  $g$  as  $s_{j|g}$ . Following Berry (1994), the demand equation for the two-stage nested logit model is derived as follows:

For the indirect utility function shown in Formula (1),

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma v_i, \quad (2)$$

where  $D_i$  refers to consumer demographics and  $v_i$  refers to unobserved consumer attributes.  $\Pi$  is a  $K+1 \times d$  matrix of coefficients that measure how the taste of consumers vary with  $D_i$ .  $\Sigma$  is a scaling matrix.  $\theta_1 = \begin{pmatrix} \alpha \\ \beta \end{pmatrix}$  represents the average value, and  $\theta_2 = (\Pi, \Sigma, v_i)$  represents the heterogeneity.

Then we split Formula (1) into two parts:

$$u_{ijt} = \delta(X_j, P_j, \xi_{jt}; \theta_1) + \mu(X_j, P_j, D_i, v_i; \theta_2) + \varepsilon_{ijt}, \quad (3)$$

where  $\delta_{jt} = X_j \beta + P_j \alpha + \xi_{jt}$  represents the mean value, and  $\mu_{ig} = (P_j, X_j)(\Pi D_i + \Sigma v_i)$  represents HH deviations from the mean value.

$$\text{For market share } s_{jt} = \frac{\exp\{\delta_{jt}\}}{\sum_{k=0}^J \exp\{\delta_{kt}\}} \text{ and market share of the outside option } s_{ot} = \frac{1}{\sum_{k=0}^J \exp\{\delta_{kt}\}}. \quad (4)$$

$$\text{Normalize } \delta_{ot} = 0, \frac{s_{jt}}{s_{ot}} = \exp\{\delta_{jt}\}. \quad (5)$$

For easy calculation, we take logarithm for both side of equation (5) and therefore we can obtain:

$$\ln(s_{jt}) - \ln(s_{ot}) = \delta_{jt} = X_j \beta + P_j \alpha + \xi_{jt} \quad (6)$$

We then use nested logit to provide more flexible elasticity patterns:

$$\ln(s_{jt}) - \ln(s_{ot}) = X_j \beta + P_j \alpha + \ln(s_{jtlg}) \sigma + \xi_{jt}, \quad (7)$$

where  $0 < \sigma < 1$  helps illustrate the intra-group correlation in preferences.

The same product can be shown in different photos. For unobserved product characteristics in particular, one part can comprise common factors that are the same for the same products, including product-level factors (such as the degree of popularity of the product, which is presented by  $\theta_{jt}$ ) and website-level factors (such as activities provided by a website, which is presented by  $\mu_{jt}$ ). Another part includes unobserved and different factors even for the same products, which are represented by  $\varepsilon_{jt}$ . Thus, we decompose the component  $\xi_{jt}$  as:  $\xi_{jt} = \theta_{jt} + \mu_{jt} + \varepsilon_{jt}$ .

As discussed above,  $\theta_{jt}$  is a product-specific component that is the same for the same product even if they are shown by different photos, which can vary over time. This parameter contains both observed and unobserved product-specific characteristics. The observed characteristics may include season effects or product genres, as well as other observable factors. The unobserved characteristics are likely to be correlated either with the popularity of the products, quality of the products, and off-line promotions, among others. Omitting their effects will produce biased coefficients.  $\mu_{jt}$  comprises a website effect that includes website-level activities. It can be observed in consumers and is the same for all products. Given that  $\theta_{jt}$  and  $\mu_{jt}$  are the same across for the same products, their effects can cancel out by differencing the data among different photos for the same product. One product can be sold by different sellers and shown with different photos. Hence, we try to find such products among these N products to eliminate effects brought by unobserved product characteristics. Suppose we have J pairs in all and each pair has photos A and B for pair j, we obtain the following equations:

$$\ln(s_{jt}^A) - \ln(s_{ot}) = X_j^A \beta + P_j^A \alpha + \ln(s_{jtlg}^A) \sigma + \theta_{jt} + \mu_{jt} + \varepsilon_{jt}^A, \quad (8)$$

$$\ln(s_{jt}^B) - \ln(s_{ot}) = X_j^B \beta + P_j^B \alpha + \ln(s_{jtlg}^B) \sigma + \theta_{jt} + \mu_{jt} + \varepsilon_{jt}^B, \quad (9)$$

where we use superscripts A and B to represent each photo. The within-group market shares,  $\ln(s_{jtlg}^A)$  and  $\ln(s_{jtlg}^B)$ , are, by definition, endogenous and require instrumental variables. Inspired by Einav (2007) and Zhu and Zhang (2010), we use the total number of clicks at time  $t$  as the instrument for the within-group market shares. Given that A and B are from the same website, the total number of clicks is the same and can be eliminated through the differencing process. In addition, product price,  $P_{jt}^A$  and  $P_{jt}^B$ , can be endogenous in our demand model. Price may correlate with product characteristics, such as the quality of product, popularity of product, and product photo. As Berry (1994) and Nair et al. (2004) suggested, we use product characteristics as instruments. One part of the observed product characteristics is represented by  $X_j^A$  and  $X_j^B$ ; the other part of the observed product characteristics can be found in  $\theta_{jt}$ . The unobserved part of product characteristics, such as the quality of the product and the popularity of the product, can also be found in  $\theta_{jt}$ . Therefore, we eliminate the product-specific effects  $\theta_{jt}$  and website-level effects  $\mu_{jt}$  by differencing the data across pairs:

$$\Delta M_{jt} = \Delta X_j \beta + \Delta P_j \alpha + \Delta \ln(s_{jtlg}) \sigma + \varepsilon_{jt} \quad (10)$$

where  $\Delta M_{jt} = \ln(s_{jt}^A) - \ln(s_{jt}^B)$ ,  $\Delta X_j = X_j^A - X_j^B$ ,  $\Delta P_{jt} = P_{jt}^A - P_{jt}^B$ ,  $\Delta \ln(s_{jtlg}) = \ln(s_{jtlg}^A) - \ln(s_{jtlg}^B)$ .

The product-specific effect (e.g., the popularity of product) is important for customers but is difficult for researchers to measure. Website-level effects, such as activities held by a website, can also influence the click behavior of consumers. Capturing the influence brought by a website is difficult. Our DID approach will eliminate their impact.

## Empirical Analysis and Results

### Data

Construct	Variable	Explanation
Color	<i>Lightness</i>	Average lightness of product photo
	<i>Saturation</i>	Average saturation of product photo
	<i>CoolColorRatio</i>	Ratio of cool colors with hue ([30–110]) in the HSV space
	<i>ClearColorRatio</i>	Ratio of colors with brightness ([0–1]) greater than 0.7
Space	<i>LARatio</i>	Largest area ratio of the product photo
	<i>VerticalRoT</i>	Distance to the first vertical trisection line, normalized by the total number of pixels
	<i>HorizontalRoT</i>	Distance to the first horizontal trisection line, normalized by the total number of pixels
Complexity	<i>Kurto</i>	Degree of kurtosis for product photo
	<i>NumSIFT</i>	Number of key points on the product photo
	<i>Contrast</i>	Texture contrast of product photo
Human	<i>NumHumanFace</i>	Number of human faces on the product photo

Founded in 2011, Mogujie is now one of the largest social shopping website in China, with more than 20 million registered users. In this research, we obtained real click data for the detailed page view from Mogujie Company. The dataset contains click information for detailed page views for a half-year period, from June 30, 2014 to December 26, 2014. The products come from two categories: clothes and shoes. The clothes category has approximately 20,000 products, and the shoe category has approximately 14,000 products. We hired a research assistant to code the product photos and found 354 pairs of clothes photos and 1021 pairs of shoes photos. One product may have more than two Webpages and thus generate more than one matched pair. We considered all combinations of the photos of a same product to generate the matched pairs, and each pair was recorded in our econometric model. We obtained the number of clicks for detailed page view from the PC. We use clicks for detailed page view (i.e. NumDPV) to compute dependent variables because it is a typical signal indicating a user's interest for a product.

Variable	Clothes category shown by Photo A				Shoes category shown by Photo A			
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
<i>NumDPV</i>	2.82132	11.6252	0	380	1.39041	4.51090	0	114
<i>Price</i>	95.9225	37.2693	25	306.6	147.730	57.7143	39	468
<i>Lightness</i>	0.56318	0.11777	0.24557	0.8320	0.75304	0.07582	0.49805	0.9278
<i>Saturation</i>	0.27281	0.11670	0.07987	0.76363	0.30587	0.12712	0.05451	0.8885
<i>CoolColorRatio</i>	0.31993	0.20945	0.00181	0.8784	0.34398	0.23771	0.00029	0.9788
<i>ClearColorRatio</i>	0.44523	0.17938	0.01547	0.9274	0.70213	0.11985	0.14492	0.9730
<i>LARatio</i>	0.43233	0.0588	0.19742	0.57638	0.41881	0.03409	0.25965	0.52121
<i>VerticalRoT</i>	0.00053	0.00017	0.0000	0.00123	0.00057	0.00014	0.0001	0.00161
<i>HorizontalRoT</i>	0.0008	0.00035	0.0000	0.00199	0.00092	0.00024	0	0.00221
<i>Kurto</i>	2.13256	1.13853	1.1811	10.1629	3.89201	2.06311	1.2438	20.6536
<i>NumSIFT</i>	223.90	56.3292	50	557	188.387	37.6289	61	299
<i>Contrast</i>	0.45644	0.52764	0.1165	5.6261	0.22788	0.10631	0.0444	1.2007
<i>NumHumanFace</i>	0.41243	0.58737	0	2	0.33790	0.53176	0	2

Table 1 shows the variables for photo characteristics and Table 2 show descriptive statistics.

### Regression results

Table 3 present the GMM regression results based on the DID specification in Equation (10). We use  $\ln(s_{jt|g}^A) - \ln(s_{jt|g}^B)$  as dependent variables in all models. Product photos with aesthetical color, appropriate composition, and proper complexity induce more clicks from users. Particularly for the clothes category, a photo with warm color, rule of thirds and great complexity will gain more clicks from users. For the shoes category: a photo having high lightness, large key object and high contrast will attract more clicks from users.

<b>Table 3. Results for clothes category and shoes category</b>		
	Clothes	Shoes
$\Delta Price$	-0.0008(0.001303)	0.002649(0.000646)***
$\Delta Within\text{-}group\ share$	1.533464(0.034563)***	1.631783(0.008941)***
$\Delta Lightness$	0.00441(1.5068)	0.834927(0.47142)*
$\Delta Saturation$	-0.14179(0.699776)	-0.11002(0.1446)
$\Delta CoolColorRatio$	-1.00528(0.352106)**	-0.03548(0.085773)
$\Delta ClearColorRatio$	0.419852(0.981633)	-0.45993(0.351223)
$\Delta LARatio$	1.216537(1.09175)	1.405126(0.728642)*
$\Delta VerticalRoT$	-133.428(152.2656)	-128.719(146.4573)
$\Delta HorizontalRoT$	-175.283(97.67506)*	82.91501(86.39768)
$\Delta Kurto$	0.019164(0.055354)	0.023632(0.01428)*
$\Delta NumSIFT$	0.00475(0.001352)***	-0.00047(0.000438)
$\Delta Contrast$	0.023207(0.103746)	0.296624(0.11013)**
$\Delta NumHumanFace$	-0.04209(0.07067)	0.024275(0.029051)
* p<0.1, ** p<0.05, *** p<0.01 (Robust standard errors in parentheses)		

### Conclusion

In this research, we study how visual aesthetics delivered through product photos can be captured with the help of modern image-processing techniques and how product photos affect users' shopping behavior in a social shopping context. We design variables that capture photo aesthetics related to four facets: color, composition, complexity, and model face. We build econometric models to carefully gauge the causal relationship between photo features and consumer shopping behavior. The initial results show that visual product presentation influences consumer shopping behavior.

This research provides several theoretical contributions. First, we build a framework that maps photo features extracted by image-processing techniques with theories developed in HCI and psychology. This research systematically studies the determinants of online shopping behavior unique to the e-commerce context, namely, product visual presentation. Consumers in online stores and physical stores consider several factors, such as product brand, quality, functionality, price, and the product's reputation, when making purchase decisions. However, in a physical store, consumers usually have direct access to the product; in an online store, consumers usually rely on the provided product photos and descriptions to judge a product. Product presentation is an extra dimension that retailers can manipulate to influence e-commerce consumers. Limited literature is available on this problem, and the present study fills this void. Second, this research participates in the growing trend of big data research, which utilizes large volumes of heterogeneous data to address significant practical problems. Specifically, this research integrates multimedia data from the e-commerce environment with transactional business data to address a high-impact problem in marketing, online consumer shopping behavior. Third, this research is impossible to conduct without image-processing technologies that can handle the large volume of image data. Finally, this research also requires strict econometrics analyses to establish a causal relationship. The research



draws attention to using image-processing techniques to study human behavior through large-scale empirical studies.

This research also has significant implications for the practice of e-commerce, especially for retailers in an e-commerce marketplace. A small retailer generally has few means to affect customers in an e-commerce marketplace; one of these means is product description. Owing to the intangibility of online shopping, consumers frequently rely on product descriptions provided by retailers to assess the quality or functionalities of the product. Furthermore, small retailers often rely on their personal experience in choosing product photos to present. This practice limits effective communication between retailers and consumers, and creates a competitive disadvantage for less experienced retailers. This research provides quantitative assessments of product photos that can be measured by using image-processing software. Results of this research can be used to predict the marketing effectiveness of provided product photos and direct the product presentations in e-commerce websites. Results of this study may contribute to the development of software that can assist retailers in selecting product photos that can prompt higher sales. Considering that consumers' focus on different visual stimuli may change over time, this computer-aided approach may assist retailers in keeping up with changing trends.

In the future, we will improve the econometric model. A multiple discrete choice model is necessary if consumers click more than one product on the same day. We will also develop other measures to analyze visual information in the context of behavioral theories. Our ultimate goal is to develop a framework that uses image-processing techniques to discover the effect of visual features on consumer behavior, which can also be used by e-commerce stores to improve sales.

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