Photos that Click: Curating Photographic UGC to Increase Visitor Engagement and Product Exploration on Websites

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Abstract

Despite the enormous growth in images shared among consumers on social media such as Instagram and Facebook, most forms of consumer-to-consumer influence continue to be analyzed under the umbrella of word of mouth. There is therefore a pressing need for an alternative framework for formal investigations of visual forms of consumer-to-consumer interactions. This is the gap that we address in this research. We develop a theoretical framework based on the stimulus-organism-response theory to describe and analyze how photographic user generated content affects consumer response. We then use the framework to empirically identify how three attributes of photographic UGC – colors, visual complexity and authenticity - affect consumers’ interest in the images and further exploration of the pictured products.

Close to six thousand images (5952) of fifteen brands across six categories posted by consumers on the social network Instagram serve as our research setting. We monitor two rates of response to these images by visitors when they are posted by the brands on their websites: (1) engagement with the images through actions such as viewing or additional exploration (e.g., enlarging them on the screen to get a better view) and (2) subsequent to the engagement, further exploring the webpage of the specific product displayed in the image.

We use MATLAB’s Image Processing Toolbox to obtain the three measures of color (hue, chroma and lightness) in the CIELab color-space across six hues - red, yellow, green, cyan, blue, and violet – for each image in our sample. We then investigate how the response rates for each image are related to its color characteristics, visual complexity, and authenticity while controlling for the roles of the brands (through fixed effects) as well as for multiple sources of endogeneity.

We assume that the two response-rates follow a Beta distribution. One of the empirical challenges with our response rate data is that, for some photos, we have interaction rates of 1. We also have a large number of photos for which the exploration rate is zero. We therefore use the one-inflated and zero-inflated Beta distributions to handle these characteristics of the two response rates and use Bayesian Beta regressions for our analysis.

Our results suggest that the color green has a significant positive effect on engagement while yellow and blue positively affect visitors’ interest in further exploring the displayed product. We also find that an increase in the overall visual complexity of the photo – measured as variations in brightness and depth of the colors – improves both engagement and product exploration. Additionally, images that are not authentic but manipulated to alter their characteristics before they are shared lose their ability to attract engagement and exploration. We also assess the validity of our findings through predictive testing of consumer response to a holdout sample of 2090 images.

We demonstrate the managerial application of our findings by developing and implementing an algorithm for online firms to curate collections of photos of products posted by customers in social media.

Keywords: Social Media, Visual UGC, Colors, Visual Complexity, Authenticity, Inflated Beta Distributions, Bayesian Beta Regressions, Curation, Photo Galleries
“Recent research in consumer behavior has begun to focus on visual imagery in advertising (Edell and Staelin 1983; Kisielius 1982), but personal influence of a visual form and its functioning remains an untapped research area.”

(Gatignon and Robertson 1985, p. 856)

It has been almost three decades since this call by Gatignon and Robertson (1985) but personal visual influence has not attracted much attention from marketing scholars during this period. Despite the enormous growth in images shared among consumers on social media such as Instagram and Facebook, most forms of consumer-to-consumer influence continue to be analyzed under the umbrella of word of mouth. For instance, the number of images posted on just the two popular image-sharing sites Pinterest and Instagram total about 10 million per day (Domo 2013).

By definition, word of mouth focuses on the verbal and semantic elements, and not the visual aspects, of consumers’ influence on other consumers. As suggested by Yadav and Pavlou (2014) recently, there is therefore a pressing need for an alternative framework for formal investigations of visual forms of consumer-to-consumer interactions:

“The second gap in the literature pertains to an important shift in the type of content generation that seems to be occurring in social networks. The shift is from primarily text-based UGC to newer types of curated collections that feature more complex multimedia collections. For example, Pinterest allows users to create and share collections of product images. ... Despite the increasing interest in curated collections, many questions remain about how they can be monetized or leveraged for marketing purposes.”

This is the gap that we address in this research. More particularly, we have two goals. Our first goal is to develop a theoretical framework to describe and analyze how photographic user generated content affects consumer response. Our second, empirical, goal is to use the framework to identify attributes of
photographic UGC that stimulate consumers’ interest in the images and further exploration of the pictured products.

Our research proceeds through three stages. In the first stage, we develop our theoretical framework to describe consumer response to images shared by other consumers. We rely on the stimulus-organism-response (SOR) theory (Mehrabian and Russell 1974) for our development. Two features of the theory make it the most relevant for photographic UGC. One, individuals respond to stimuli from the objects that they are exposed to. Several findings in the literature suggest that the characteristics of images affect viewer response (Gorn et al 1997, Lohse and Rosen 2001, Mehta and Zhu 2009, Meyers-Levy and Peracchio 1995, Pieters, Wedel and Batra 2010, Schindler 1986, Sparkman and Austin 1980). Thus, images and their characteristics serve as the objects and stimuli in our framework. Two, the theory suggests that there are two types of response, approach and avoidance, to the objects. In the case of photographic UGC, engagement with the photos, and further exploration or purchase of the pictured products, represents approach. Not engaging in either action, on the other hand, indicates avoidance.

In stage two, we empirically investigate how three attributes of photos - colors (Valdez and Mehrabian 1994), visual complexity (Pieters, Wedel and Batra 2010), and authenticity (Stern 1994) – act as stimuli that affect consumer response. We consider these attributes of photos as stimuli based on findings in the literature. Thus, the color of an object has been found to have the most significant effect on exploratory response (Dondis 1973, Elliott et al 2009, Turley and Millman 2000). Color also has a strong influence on behavioral responses in a variety of contexts. For instance, Belizzi and Hite (1992) find that consumers’ decisions to purchase after browsing in a store are affected by the colors of the retail environment. In a very different context, Garrett and Brooks (1987) find that how individuals vote
for a candidate depends on the color of the ballot – men tend to vote more for candidates whose names appear on green ballots while women are more likely to vote for candidates listed on pink ballots.

Visual complexity serves as our second stimulus. Visual theorists (Donnis 1973) suggest that viewers’ attitudes towards an image are significantly affected by its complexity. This is a consequence of the demands placed on the viewers’ cognitive resources by more complex images (Peracchio and Levy 1994). Additional empirical evidence of the effects of visual complexity is also provided by recent findings on consumer response to advertising (Pieters, Wedel and Batra 2010, Teixeira, Wedel, and Pieters 2012).

We choose authenticity as our third stimulus since it has a significant effect on how consumers respond to product communications and visual imagery (Beverland et al 2008, Brown, Kozinets and Sherry 2003, Grayson and Martinec 2004, Rose and Wood 2005). In fact, several findings in the literature suggest that perceived lack of authenticity leads to avoidance of advertising (Chalmers 2007) and even of products (Lee et al 2009, Thomson et al 2006).

Close to six thousand images (5952) of fifteen brands across six categories posted by consumers on the social network Instagram serve as our research setting. We monitor two rates of response to these images by visitors when they are posted by the brands on their websites: (1) engagement with the images through actions such as viewing or additional exploration (e.g., enlarging them on the screen to get a better view) and (2) subsequent to the engagement, further exploring the webpage of the specific product displayed in the image. We then investigate how the response to each image is related to the levels of the three stimuli included therein while controlling for the roles of the brands (through fixed effects) as well as multiple sources of endogeneity.

We assume that the two response-rates follow a Beta distribution (Johnson, Kotz and Balakrishnan, 1995, p. 235). One of the empirical challenges with our response rate data is that, for some photos, we
have interaction rates of 1. We also have a large number of photos for which the exploration rate is zero. We therefore use the one-inflated and zero-inflated Beta distributions (Ospina and Ferrari 2007) to handle these characteristics of the two response rates and use Bayesian Beta regressions (Ferrari and Cribari-Neto 2004) for our analysis.

Our results suggest that the color green has a significant positive effect on engagement while yellow and blue positively affect visitors’ interest in further exploring the displayed product. We also find that an increase in the overall visual complexity of the photo – measured as variations in brightness and depth of the colors – improves both engagement and product exploration. Additionally, images that are not authentic but manipulated to alter their characteristics before they are shared lose their ability to attract engagement and exploration. We also assess the validity of our findings through predictive testing of consumer response to a holdout sample of 2090 images.

The third stage of our research is focused on managerial application of our findings. Specifically, we develop an approach for firms to rapidly curate and update photographic user generated content to reach targeted levels of engagement and exploration by visitors to their websites. We also demonstrate our approach with a curated gallery.

In the next section, we first present our theoretical framework and also develop the theoretical background to guide our selection of independent variables in the models for the two response rates. We follow this with a description of our data and then of our model for our empirical analysis. We next present our results and their managerial application. We conclude with a discussion of the limitations and opportunities for future research.
2. Theoretical Framework

**Stimulus-Organism-Response (SOR) Theory**

The Stimulus-Organism-Response (SOR) theory, first proposed by Mehrabian and Russell (1974), has been applied widely in marketing (e.g., Belk 1975, Rossiter and Percy 1978, Buckley 1991, Baker, Levy and Grewal 1992, Sherman, Mathur, and Smith 1997). The core of the theory that environmental stimuli (S) lead organisms (O) to respond (R) has found empirical support in investigations of various marketing stimuli including product attributes (Bloch, 1995, Lai, 1991), service attributes (Foxall and Greenley, 1999 Jang and Namkung 2009), brick-and-mortar store environments (Baker, Levy, and Grewal 1992), features of online stores (Eroglu, Machleit, and Davis, 2001, Mummalaneni, 2005), design aspects of websites (Wang et al 2007) and price (Ziethaml 1982). Jacoby (2002) reviews several applications and concludes that the theory has “provided the foundation for the social and managerial sciences” (p.56) since its introduction.

The most extensive use of the S-O-R theory, however, has been in the retailing context following its application by Donovan and Rossiter (1982) to explain in-store behavior of retail consumers. Donovan and Rossiter (1982) find that elements of the retailing context like merchandise layout, lighting, music, and color in the store act as stimuli that affect whether consumers stay, explore, and buy from the store (i.e., approach responses) or leave the store without exploring, interacting with the store personnel, or making a purchase (i.e., avoidance responses). The theory has also been used to investigate consumer response in the online retailing context (Eroglu, Machleit, and Davis 2003, Ha and Lennon 2010).

**Color**

Psychologists have known for almost a century that color plays an important role in emotions (Dashiell 1917). Its potential role in marketing and consumer response was also recognized (Kotler 1973)
and empirically investigated in various contexts. For instance, Bellizzi et al (1983) and Bellizzi and Hite (1992) find that color plays a significant role in consumer behavior in brick-and-mortar retailing; the time spent in the store exploring and shopping and the number of purchases made is higher in stores with more tones of blue in their interiors than stores where red is the more dominant color (Bellizzi and Hite 1992). Subsequent studies by Crowley (1993) and Babin et al (2004) confirm the positive role played by blue interiors on retail shopping behavior in traditional retail stores. Additionally, investigations of the role of colors in online retailing (Eroglu et al 2003, Ha and Lennon 2010) provide further evidence that the colors used in various part of online retail sites such as the site background or text font affect browsing and shopping behavior.

Additional evidence of the role of colors in consumer response is reported in the advertising context (Gorn et al 1997, Lohse and Rosen 2001, Mehta and Zhu 2009, Meyers-Levy and Peracchio 1995, Schindler 1986, Sparkman and Austin 1980). Rather than limiting the investigations to how hues such as blue, red or yellow affect behavior, research in advertising has also considered the roles of chroma which measures the depth of each hue (e.g., extreme blue vs. light blue) and lightness which represents whether a color is bright or dark. Gorn et al (1997), for instance, find that the color blue elicits more relaxation while viewing an ad but this feeling does not translate either into higher likability of the ad or of the advertised brand. In contrast, higher chroma of colors results in greater excitement and higher liking for the ad but not for the advertised brand, while increased brightness of colors leads to greater feelings of relaxation and liking for the ad and the advertised brand.

**Visual Complexity**

The complexity of stimuli affects how individuals respond to them (Mehrabian 1977, Sokolov 1960, 1963). This is also true for stimuli processed by consumers. Some studies find, for instance, that consumers respond positively to the design complexity of products (Landwehr et al 2010, 2013).
Similarly, the visual complexity of images in print advertising (Morrison and Dainoff 1972, Peracchio and Meyers-Levey 1994, Pieters, Wedel and Batra 2010), television and video-based advertising (Teixeira et al 2012) and retail interiors (Orth and Wirtz 2014) affects consumer response.

Visual complexity theory (Attneave 1994, Donderi 2006) is based in the idea that visual stimuli like images are a composite of different elements including colors, depth of the colors, brightness, and the type and number of objects and patterns included (Pieters et al 2010). An increase in the number or variation of one or more of these components increases the size of the image in terms of computer memory required and its visual complexity. Thus, an image with more colors or with more variations of brightness would be more complex than one with fewer colors or uniform brightness. Similarly, an image with variations in the depth of colors is more complex than one with more uniformity in the depth.

Findings regarding the effects of visual complexity on consumers are mixed. For instance, Chamblee et al (1993) and Putrevu et al (2004) find that increased visual complexity motivates consumers to spend more time viewing and processing the information and leads to better comprehension of the message. Similarly, Peracchio and Meyers-Levy (1994) find that increasing visual complexity by cropping the images of products in the ads enhances consumers’ evaluation of the advertised products. Teixeira et al’s (2012) findings, on the other hand, suggest that high levels of complexity lead to avoidance of video ads. Similarly, Pieters et al (2012) find that increasing the complexity in terms of the number of colors and variations in brightness hurts the attitude towards the ad and results in reduced attention to the advertised brand.

**Authenticity**

Authenticity is a focus of research in multiple disciplines including anthropology (Bruner 1994), cultural studies (Vannini and Williams 2009), philosophy (Trilling 1971, Taylor 1991), archaeology
(Harrison 2000), tourism (MacCannell 1973), literary criticism (Donovan 1998) and sociology (Finch 1987). It can play a significant role in consumer response to advertising (Beverland et al 2008, Chalmers 2007), product offerings (Grayson and Martinec 2004), brands (Chiu et al 2012) and service providers (Price, Arnould and Tierney 1995).

The perceived authenticity of an object - its perceived genuineness (Rose and Wood 2005, Trilling 1971) and the assessment of whether it is “genuine, real and/or true” (Beverland and Farrelly 2010, p.839) – affects how individuals respond to it (Rose and Wood 2005). Importantly, perceptions of genuineness are formed from visual stimuli. Beverland et al (2008), for instance, find that respondent assessments of the authenticity of advertising claims regarding the long and historic tradition of a Belgian brand of beer are affected by visual cues such as the type of clothes worn by those serving the beer in the pictured ad, the beer being served from a tap, and the estimated age of the picture based on the type of elements it includes in the background (e.g., an old trolley).

The findings and conclusions on the role of perceived authenticity in consumer response are quite consistent. An increase in authenticity enhances positive response (Beverland et al 2008, Holt 2002, Newman and Dhar 2014, Steenkamp et al 2010, Sirianni et al 2013). Conversely, a reduction in perceived authenticity leads to negative responses such as loss of trust and negative attitudes (Lunardo and Mbengue 2013).

Authenticity is an important construct in our context since social media sites like Instagram and Twitter allow consumers to use filters (The Atlantic 2012, Twitter 2012) to change the three basic traits – color, chroma and brightness - of their photos before posting them. Interestingly, the use of filters is viewed by many users of social media as being inauthentic (The Guardian 2012). The absence of the text #Nofilter in the caption of a posted image indicates to the viewers that it has been altered with a filter.
**Conceptual Model**

Figure 1 presents our conceptual model of how user generated social media images affect response by visitors when they are posted on a firm’s website. A visitor arriving at the site sees images of the firm’s products posted by other consumers on social media but collected and curated by the firm on its site (see Figure 2 for an example of a curated gallery). The colors, visual complexity and authenticity of the images are the stimuli that we investigate in this study. These are, however, not all of the stimuli that the visitor is exposed to. Other stimuli that affect her include other attributes of the images such as the number and types of objects included in the images (Pieters et al 2010), presence or absence of human subjects, emotions displayed by the subjects (Burke and Edell 1989), quality of the photography and so on.

---- Figures 1 and 2 about here ----

Other images on the website and the attributes of the website (e.g., color and size of the text in the content) are additional stimuli that the visitor is exposed to. In addition, visitor response is also likely to be affected by the following factors:

1. Captions and comments added by consumers who posted the images.

2. Influence of the consumer posting the image - since some consumers may be more influential and may stimulate more engagement and exploration with their postings than others (Kozinets et al 2010).

3. Product category - since some categories such as fashion and clothing may stimulate more exploration than others.
(4) Brand characteristics - such as brand personality (Aaker 1997), presence on social media (e.g., having a fan page on the site Facebook) and level of promotional expenditures all of which may affect engagement and/or exploration.

(5) Visitor characteristics - such as demographics and purchase readiness stage (Framback et al 2007).

(6) Day and time of visit - which could affect consumer online activities (Rutz and Bucklin 2011).

(7) Duration for which the image has been on the website - since an increase in duration may increase repeat exposures and affect engagement and exploration.

(8) Number of photos in the gallery - since individual images in larger galleries face greater competition for viewer interest and, hence, for engagement and exploration.

Since our second research goal is to identify the colors, visual complexity, and authenticity of photographic UGC that stimulate website visitors’ interest in the images and further exploration of the pictured products. We therefore need to control for the role of all the factors listed above in our empirical investigation as potential sources of endogeneity. We discuss this issue further in the following two sections.

3. Data and Variables

Overview of the Data

The data for our empirical analysis is provided by a technology company, TECH (name disguised to maintain confidentiality) that searches the social media site Instagram for images that include products and supplies them to firms that market those products. Firms that purchase the service curate and post some of them on their websites as curated galleries that include multiple images (Figure 2). Visitors to the site can scroll through the galleries to view one or more of the included images.
TECH also installs software on the firms’ sites to track the number of visitors and their interaction with the images. Specifically, the software tracks (1) the specific images included in the gallery (2) the number of images included (3) for every image in the gallery, the number of visitors who engaged with it through actions such as placing the cursor on the image, enlarging the image, or clicking on it (4) the number of visitors who, after engaging with an image, proceeded to the pictured product’s page to further explore and purchase the product. For each image in the gallery, the software provides daily reports on the proportion of visitors to the site who (1) engaged with it (the engagement rate) and (2) visited the web page of the product included in the image to further explore and purchase it (the exploration rate).

Dataset

Our sample includes 8042 digital images posted on the social media site Instagram by customers of 15 firms across six product categories including cosmetics, shoes, clothing, exercise apparel, jewelry and news. Between these firms, the prices of the products marketed ranged from $6.00 to $1300 dollars. Some of the firms also had highly diverse product mixes in terms of functions. One firm, for instance, had a product mix with prices between $50 and $1300. The customers of the firms are also therefore likely to be diverse both within and across firms. We relied on this diversity of categories, brands, product mixes, prices and customers in our sample as one control for endogeneity. The diversity reduces the likelihood of systematic correlation between the included variables (e.g., colors, complexity and authenticity) and omitted variables such as brand, website, price or visitor characteristics.

The images were displayed by the firms in galleries of five or more images on their websites. We also had data on the engagement and exploration rates for each image in the sample. Additionally, for every image in the sample, we had the text of the caption used by the consumer posting the image and a record of whether the image was posted as it was or was modified with one of the filters provided.
by Instagram before it was posted. Finally, we also had a record of the number of days for which the image has been posted on the site by the time the engagement and exploration rate measures were collected. We selected a random sample of 5952 images for calibrating our empirical model and used the remaining 2090 images for predictive testing of the model.

Variables

Colors

A digital image is a mosaic of millions of pixels (Blinn 2005). Each pixel is encoded with information on (1) hue – the color carried by the pixel (2) chroma – the depth of the hue in the pixel with higher values corresponding to greater depth (3) lightness - how bright or dark the hue is (Othman and Martinez 2008). We use MATLAB’s Image Processing Toolbox (MATLAB 2013) to obtain the three measures in the CIELch color-space (Kuehni 2003) across six hues - red, yellow, green, cyan, blue, and violet – for each image in our sample. Specifically, for each image, we compute the following eighteen variables:

1. \( P_H \) = Proportion of all the pixels that carry hue \( H \), \( H = \) red, yellow, green, cyan, blue, violet; \( 0 \leq P_H \leq 1 \).
2. \( C_H \) = mean chroma of the pixels that carry hue \( H \); \( 0 \leq C_H \leq 100 \) with higher values indicating higher depth of the hue.
3. \( L_H \) = mean lightness of the pixels that carry hue \( H \); \( 0 \leq L_H \leq 100 \) with higher values indicating higher lightness.

Visual Complexity

The size of an image in terms of the digital memory that it requires as well as the variations in its hue and lightness represent visual complexity (Pieters et al 2010). We therefore operationalize visual complexity using the following measures:
1. Size = size of the image measured in Kilobytes

2. $CVC =$ coefficient of variation of chroma across all the pixels in the image

3. $CVL =$ coefficient of variation of lightness across all the pixels in the image

Table 1 provides a summary of the color and visual complexity variables for the calibration sample.

### Authenticity

Although Instagram offers more than 20 filters, not all are used by consumers. We selected the most used ten filters and combined the other filters into an ‘other’ category. If an image in the sample was modified using a filter, we set an indicator variable used for that filter to 1. Thus, we used 11 indicator variables, $A_l, l = 1, 11,$ to operationalize authenticity. Zeroes across all 11 variables are used to represent the case of no filter.

Unfortunately, Instagram does not provide verbal or pictorial definitions of most of the filters in the application. We therefore relied on several media firms that developed definitions. Table 2 provides a definition of each filter from these sources and the number of images in the calibration sample that were modified with that filter.

### Additional Controls for Endogeneity

**Caption:** We calculated the length of the caption in number of characters (LEN) as a proxy for how informative it is and, hence, how likely it is to attract viewer interest for the image. Additionally, since question marks might stimulate interest (Lee, Hosanagar and Nair 2013) leading to increased engagement and/or exploration, we include the presence of question marks (QUEST) in the caption as a variable. Similarly, exclamation marks may signal emotional content (Lee, Hosanagar and Nair 2013) and attract viewer interest. We therefore include the presence of exclamations (EXCL) in the caption as a variable.
Influence of Consumer Posting the Image: We obtain four measures of influence of the consumer posting the image:

1. LIKES: Number of viewers on Instagram who indicated that they like the image.
2. COMMENTS: Number of viewers who commented on the image on Instagram.
3. FOLLOWERS: Number of individuals who follow the postings of the consumer on Instagram.
4. NPHOTOS: Number of photos in all posted by the consumer up to the date on which the image was posted.

Duration: DURATION is the number of days for which the image has been on the website by the time the engagement and exploration measures were collected.

Number of photos in the gallery: GALSIZE is the number of photos in all in the gallery in which the image is included.

---- Table 3 about here ----

Model

We wish to relate the engagement and exploration rates to the color, visual complexity and authenticity of the posted images while controlling for endogeneity. Since our response variables are proportions, we assume that they follow the Beta distribution (Johnson, Kotz and Balakrishnan 1995). As suggested by Ferrari and Cribari-Neto (2004), we transform the Beta distribution into a form in which the mean can be related to explanatory variables. Formally, we assume that the engagement rate $Y_{ijk}^{EGR}$ and exploration rate $Y_{ijk}^{EXR}$ for photo $i$, in gallery $j$, of brand $k$, are distributed as

$$f(Y_{ijk}^{L}) = \frac{\Gamma(\phi^{L})}{\Gamma(\mu^{L}\phi^{L})\Gamma((1-\mu^{L})\phi^{L})} Y_{ijk}^{L} \mu^{L}\phi^{L-1} (1 - Y_{ijk}^{L})^{(1-\mu^{L})\phi^{L-1}}, 0 < Y_{ijk}^{L} < 1, L = EGR|EXR$$

(1)
\begin{align*}
E(Y_{ijk}^L) &= \mu^L \\
V(Y_{ijk}^L) &= \frac{\mu^L(1-\mu^L)}{(1+\phi^L)}
\end{align*}

\(\phi^L\) is therefore the precision parameter and we can relate \(\mu^L\) to our explanatory variables.

One constraint in relying on the Beta distribution is that its support is in \((0,1)\) and does not include either zero or one. As displayed in Figure 3, however, the interaction rate distribution of our sample contains a large number of 1’s while the shopping rates exhibit a large number of 0’s.

\[\text{---- Figure 3 about here ----}\]

We, therefore, turn to the one-inflated and zero-inflated Beta distributions (Ospina and Ferrari 2007) to model the two rates thus modifying the unconstrained Beta distribution into a mixture of two components: a degenerate distribution for zero or one as the case maybe and the unconstrained Beta distributions:

\[
f(Y_{ijk}^L) = \alpha_{\text{EGR}}, \text{if } Y_{ijk}^L = 1 \text{ and } L = \text{EGR} \\
= \alpha_{\text{EXR}}, \text{if } Y_{ijk}^L = 0 \text{ and } L = \text{EXR} \\
= (1 - \alpha_L) \cdot \left[ \frac{\Gamma(\phi^L)}{\Gamma(\mu^L \phi^L) \Gamma((1-\mu^L) \phi^L)} Y_{ijk}^L \mu^L \phi^L - 1 \right] (1 - Y_{ijk}^L)^{(1-\mu^L) \phi^L - 1} \\
\text{if } 0 < Y_{ijk}^L < 1, L = \text{EGR}|\text{EXR} \]

The distributions thus have three parameters \(\Theta^L = (\alpha_L, L = \text{EGR}|\text{EXR}; \mu^L; \phi^L)\). We therefore write the Likelihood of a sample of N observations as the product of two parts – one arising from the degenerate distribution and the other from the unconstrained Beta distribution:

\[
L(\Theta^L) = L_1(\alpha_L).L_2(\mu^L, \phi^L) \\
L_1(\alpha_L) = \prod_{i=1}^{N} \alpha_L^{I_{LY_{ijk}}}(1 - \alpha_L)^{1 - I_{LY_{ijk}}}
\]
where \( N_L, L = EGR|EXR \), is the number of observations where the engagement rate, \( EGR = 1 \), or the shopping rate, \( EXR = 1 \) and \( \alpha_L^{1_LY_{i,j,k}} = 1 \) if \( Y_{i,j,k} = L \) and zero otherwise.

\[
L_2(\mu^L, \phi^L) = \prod_{i=1}^{N} f(Y_{i,j,k}^{L})^{(1-L)}}^{L}Y_{i,j,k})
\]

Link

To estimate the effects of the explanatory variables, we relate them to the mean \( \mu^L \) of each distribution. Specifically, following Ferrari and Cribari-Neto (2004) we use a Logit link of the explanatory variables to model the interaction and shopping rates as follows:

\[
\text{Logit}(\mu_{i,j,k}^{L}) = \sum_H \beta_H^{L} \cdot P_{H,i,j,k} + \sum_H \beta_H^{L} \cdot (P_{H,i,j,k} \cdot C_{H,i,j,k}) + \sum_H \beta_H^{L} \cdot (P_{H,i,j,k} \cdot L_{H,i,j,k}) + \beta_S^{L} \cdot \text{Size} + \\
\beta_C^{L} \cdot \text{CVC} + \beta_C^{L} \cdot \text{CVL} + \beta_L^{L} \cdot \text{LEN} + \beta_N^{L} \cdot \text{QUEST} + \beta_N^{L} \cdot \text{EXCL} + \\
\sum_{N=1,11} \beta_A^{L} \cdot A_{N,i,j,k} + \beta_L^{L} \cdot \log(\text{LIKES}) + \beta_L^{L} \cdot \log(\text{COMMENTS}) + \\
\beta_L^{L} \cdot \log(\text{FOLLOWERS}) + \beta_L^{L} \cdot \log(\text{PHOTOS}) + \\
\beta_L^{L} \cdot \log(\text{DURATION}) + \beta_L^{L} \cdot \log(\text{GALSIZE}) + \gamma_k + \delta_{i,j,k}^{L}
\]

We include the chroma and lightness variables for each hue via interactions with the proportion of that hue in the image. This permits the chroma and lightness of hues with higher proportions to have a larger effect. \( \gamma_k \) is the fixed effect of brand \( k \). We include this as an additional control for endogeneity to capture the effects of the brand variables included in our conceptual model but omitted from the specification of the link. It should also absorb some of the effects of other brand-related variables like the characteristics of its customers and visitors since these are likely to vary across brands. We include \( \delta_{i,j,k}^{L} \sim N(0, \tau^L) \), the random effect of gallery \( j \) of brand \( k \) for \( L = EGR|EXR \), as an additional control for endogeneity related to the effects of the galleries themselves on the exploration and engagement rates of the images that they include. For instance, a gallery that includes photos that contain a specific combination of filters may have different effects on its photos than those that contain other
combinations. Similarly, galleries that include photos of some products may affect their photos differently than those that have other products.

We calibrate the model in a Bayesian framework with normal priors on all the parameters in the link, a $U[0,1]$ prior on the inflation parameters, $\alpha_L$, $L = \text{EGR|EXR}$, and Gamma priors on the parameters, $\phi^L$, $L = \text{EGR|EXR}$ and the precision parameter, $\tau^L_0$, for the random effects of the galleries. All the priors are uninformative and highly diffuse.

Results

Model Selection

Colors and captions are the most visible attributes of the images to the visitors to the sites. We therefore calibrated two nested versions of the exploration and engagement rate models – one with only the color attributes and another with color and text attributes of the captions – to investigate whether we can rely only just on these two sets of attributes to explain the two rates and thus have a parsimonious specification. The fits of the nested and full versions, the Mean Square Error in their predictions of the rates, and the performance of the shopping-rate component of each version in predicting the proportion of zeroes in the data, are summarized in Table 4.

--- Table 4 about here ---

A review of the table suggests that the full version is preferable for both the engagement rate and exploration rate models. We therefore select this version for both rates and discuss the parameters next.

Engagement Rate

Estimates of the parameters of the engagement rate model are presented in Table 5.
**Colors:** We cannot include all six colors in the model since, between them, they represent all the pixels in the image. Thus, including all colors will make the model parameters unidentifiable. We therefore used violet as the baseline. The posterior summaries of the parameters for colors indicate that two of the six hues affect the rate of engagement with the image either directly or through the interaction with chroma or lightness. Of these, red has a significant, negative, main effect. This is similar to previous findings in the literature (Belizzi, Crowley and Hasty 1983) that red is seen as more negative and stressful than green which generates more positive feelings such as ‘cool’ and ‘welcoming’ in retail consumers. In fact, investigations in several disciplines over many decades have suggested that red has more negative effects compared to other colors (Clynes and Kohn 1968, Gerard 1957) while green is found to be one of the most pleasant (Valdez and Mehrabian 1994) colors that has calming effects and reduces stress (Jalil et al 2012).

Interestingly, however, the effects of chroma are positive for both red and green, although the effect for green is almost three times as large. Thus, an increase in the depth of either hue increases the rate of engagement. These effects are also consistent with earlier findings regarding the role of depth. For instance, Valdez and Mehrabian (1994) report that increases in chroma are more arousing. Another finding that is very interesting, and consistent with prior findings in color research, is the combination of a positive effect of chroma and a negative effect of brightness for green. A combination of higher chroma and lower brightness is seen as more warm and stimulates more activity (Hogg 1969, Valdez and Mehrabian 1994) than the combination of lower chroma and higher brightness, which is a cooler and activity-reducing combination.

**Visual Complexity:** The estimate for only one of the three measures of visual complexity is significant and is positive. Thus, increased variations in the brightness of the hues across the image...
increase viewer engagement. Our finding is thus consistent with the school of thought in research on advertising that visual complexity increases viewer engagement (Chamblee et al 1993, Peracchio and Meyers-Levy 1994, Putrevu et al 2004).

**Authenticity:** Of the ten Instagram filters included in the model, only three have significant effects on the engagement rate and, of the three, two are negative. Since the no-filter case is the baseline, the estimates of the filter variables indicate that, overall, photos without filters generate more engagement.

**Controls for Endogeneity:** Several of the variables included as controls for endogeneity have significant effects thus serving their purpose. For instance, of the three variables representing the characteristics of the caption, the parameter for the presence of question marks is significant and positive. This suggests that photos with one or more question marks in their caption will stimulate more engagement while the presence of exclamation marks has no effect.

The parameters for the effects of both measures of response to a photo in Instagram on engagement rate are not significant. This is an interesting finding in that it suggests that firms should not rely on viewer reaction in Instagram to select photos for curated collections. In contrast, the estimated effect of the number of days suggests that photos that have been in a curated collection for a longer time will generate more engagement. Similarly, the estimate for the size of the gallery indicates that larger galleries have higher engagement rates for the included images. Interestingly, the number of followers of the consumer posting the image on Instagram is associated with a lower engagement rate. Specifically, photos posted by consumers with a large number of followers are likely to have smaller engagement rates than those posted by others. As the number of photos posted by the consumer increases, however, the engagement rate for the photos is likely to increase.
**Random Effects and Distribution Parameters:** The table also includes estimates of the three other parameters of the model: the precision parameter, $\phi^{EGR}$, the inflation parameter, $\alpha_{EGR}$, and, $\tau^{EGR}_\phi$, the precision of the random gallery effects. The large precision parameter is an indication that the variance of the engagement rates is not very large while the small estimate of the inflation parameter suggests that the probability of observing a rate of 1 is not very high. The precision of the gallery random effects is large, relative to 1, suggesting that the unobserved effects of galleries on the likelihood of consumers’ engagement with the included photos do not vary substantially across galleries.

**Fixed Effects:** A stem plot of the posteriors of the estimated fixed effects of the fifteen brands in the sample is presented in Figure 4. The category of the brand and the number of observations in the sample corresponding to the brand are included along the left border of the plot. Only one brand has a large positive effect but the effects do vary across the brands indicating that their idiosyncratic effects are being captured.

--- Figure 4 about here ---

**Exploration Rate**

--- Table 5 about here ---

Table 5 presents estimates of the parameters of the exploration rate model.

**Colors:** The effects of colors on exploration rate are different in some aspects but similar in others to those in the case of the engagement rate. In terms of differences, the color red does not have a negative effect. Similarly, green has no effects either directly or through its chroma and brightness. On the other hand, yellow and blue have significant positive effects as opposed to the absence of any effect in the case of engagement rate. Thus, clearly, colors have very different effects on engagement and exploration rates. On the other hand, chroma has different effects for different colors as in the case
of engagement rate. Specifically, exploration rate increases with higher chroma of yellow and cyan while it decreases as the chroma of blue is increased.

Our finding is identical to the effects of the colors of retail interiors reported over three decades ago in Bellizzi et al (1983) who find that deeper colors of yellow attract more exploration from consumers while those of blue suppress the same. It is also consistent with their finding that subjects in their study find colors like yellow less pleasant and negative and, hence, more stressful to engage with but are also drawn to those colors for additional exploration. Our estimates also suggest that increased brightness of both yellow and blue reduce exploration. Thus, as in the case of engagement rate, a combination of higher chroma and lower brightness increases the rate of exploration.

**Visual Complexity:** As in the case of exploration rate, an increase in visual complexity in the form of a higher variation in the brightness of the colors across the image increases engagement rate. Thus, visual complexity has identical effects on both rates.

**Authenticity:** The effect of Instagram filters on exploration rate is similar to that on the engagement rate. Two of the three significant effects are negative suggesting that the addition of a filter to a photo reduces its ability to stimulate further exploration of the pictured product by visitors.

**Controls for Endogeneity:** The estimated effects of all included characteristics of the caption are significant but have different effects. Thus, the positive estimate for the number of words in the caption suggests that longer captions have a positive effect on engagement rate. The presence of question or exclamation marks, however, has the opposite effect.

In contrast to the case of engagement rates, an increase in the response to a photo on Instagram has a negative effect on its ability to stimulate exploration. Specifically, as the number of comments on a photo increase, the proportion of those who interact with a photo and also purchase the
included products comes down. On the other hand, an increase in the number of viewers who like a photo on Instagram is associated with greater exploration of the pictured product when the photo is posted on the website.

The estimated effect of the days for which a photo is present in a curated collection is negative as opposed to the positive effect of this variable in the case of engagement rates. Similarly, while the number of photos in a gallery increases the engagement rate of all the photos in the gallery, the effect is not significant for exploration rates. Finally, while engagement rates increase as the number of followers of the consumer posting the photo increases, the opposite is the case for exploration rates. Similarly, an increase in the number of photos posted by a consumer increases engagement rates for but decreases the exploration rates.

Random Effects and Distribution Parameters: The precision parameter is substantially smaller for this model relative to that for the engagement rate model thus indicating that the variance of the exploration rates is quite large. In contrast, the inflation parameter is quite large and indicates that the probability of observing zero exploration rates is high. The precision of the gallery random effects, however, is not much larger than 1, suggesting that the unobserved effects of galleries on the exploration rates for the photos included in them are quite dissimilar across galleries.

Fixed Effects: A stem plot of the posteriors of the estimated fixed effects of the fifteen brands in the sample is presented in Figure 5. As in the case of Figure 4, the category of the brand and the number of observations in the sample corresponding to the brand are included along the left border of the plot. The estimates in this figure are very similar to those in Figure 4. Only one brand has a large positive effect but the effects do vary across the brands indicating, in this case as well, that their idiosyncratic effects are being captured.

---- Figure 5 about here ----
**Summary:** Overall, the results for the interaction rate model suggest that visitors’ engagement with images in curated collections can be increased by photos that (1) contain higher levels of green; (2) do not contain high levels of red (3) are not very bright (4) are posted with captions that include question marks, (5) do not include filters from Instagram (with the exception of the filter lo-fi) and (6) are posted by consumers who share a large number of photos. Additionally, brands can increase interaction rates by maintaining large curated collections over long periods.

In most cases, attributes that increase engagement rates decrease exploration rates and vice versa. The results for the exploration rate model suggest that exploration rates resulting from photos in curated collections can be increased by including photos that contain (1) yellow or blue (2) higher chromas of yellow and cyan; and (3) lower brightness of yellow and blue. Additionally, photos (4) with longer captions (5) without question or exclamation marks, (6) without filters from Instagram (with the exception of some filters included in the other category of filters) (7) posted by customers who have a large number of followers but (8) do not share a large number of photos, will also have higher exploration rates. Further, brands can increase exploration rates by frequently changing the photos in the curated collections.

**Managerial Application**

We demonstrate the managerial application of our findings by developing and implementing an algorithm for online firms to curate collections of photos of products posted by customers in social media. Our algorithm proceeds as follows:

1. Select a sample of photos of the products shared in social media by customers and curate and display one or more galleries on the product website.
2. Monitor the engagement and exploration rate responses to the collections.
3. Measure the color, visual complexity and authenticity attributes of the photos as well as the endogeneity control variables for the brand in the photos.

4. Calibrate the engagement and exploration rate models for the posted galleries and obtain the parameter estimates.

5. Set a target rate, $T_{EGR}$, for interaction rate and, $T_{EXR}$, for shopping rate.

6. Select the number of photos, $N_j$, to be included in the collection.

7. Select a photo, $i=1$, posted on social media, for curated collection $j$, and forecast its interaction and shopping rates $Y_{ij}$, for $L = EGR$ and $EXR$ respectively.

8. If $Y_{ij}^{EGR} \geq T_{EGR}$ and $Y_{ij}^{EXR} \geq T_{EXR}$, retain the photo for inclusion in collection $j$; otherwise, discard the photo and select a new one; repeat until the first photo that meets or exceeds the engagement and exploration rate targets is identified.

9. Select a new photo and forecast collection-level rates $Y_j^{EGR}$ and $Y_j^{EXR}$ for the collection of previously selected photo(s) and the new photo;

   a. if the collection-level rates meet or exceed the target engagement and exploration rates, retain the new photo; otherwise, repeat until a new photo that results in collection-level rates that meet or exceed the targets is selected.

10. Repeat step (9) until $N_j$ photos are selected for the collection.

Curating based on the above algorithm will result in collections that will meet firms’ targets in terms of customer interactions with the photos and purchases of the displayed products.

**Performance Testing:** The forecasted interaction and shopping rates in steps 7 and 9 of the algorithm are key to assessing whether a photo/gallery can meet or exceed a target rate. The reliability of our algorithm in curating collections is thus affected by the quality of the model’s forecasts of
engagement and exploration rates. We therefore test the model’s performance in forecasting the two rates for the photos in our prediction sample. We compute three measures for the test:

(1) \( P_1 \) - the percent of photos for which the observed and predicted rates meet or exceed the target rates for inclusion in a curated collection.

(2) \( P_2 \) - the percent of photos for which the observed and predicted rates fall below the target rates for inclusion in a curated collection.

(3) \( P_3 \) - the percent of photos for which the model’s predictions are incorrect for either of the following two reasons:

a. The observed rates exceed, but the predicted rates fall below, the target rates; these are the observations which the model incorrectly discards from inclusion in a curated collection; this rate is thus analogous to the type II error rate.

b. The observed rates fall below, but the predicted rates are above, the target rates; these are therefore the observations which the model incorrectly recommends for inclusion in a curated collection; this rate is therefore similar to the type I error rate.

\( P_3 \) is thus the sum of the type I and type II error rates of the model.

---- Table 7 about here ----

Table 7 presents the three percentages for different target rates for engagement and exploration rates. It is clear from the table that, not surprisingly, the percent of photos selected for inclusion in curated collections falls, and the percent of photos excluded increases, as the target rates increase. The error rate also falls as the target rates increase for the exploration rate because the percent of photos selected for inclusion steadily comes down. In the case of the engagement rate, however, the error rate increases as the target rates increase perhaps because more photos are
selected due to the higher target rates. At very high target rates, on the other hand, as fewer and fewer photos are selected for inclusion, the error rate for interaction again comes down.

**Using the Algorithm for Rapid Curation and Updating of Online Product Displays:** Our algorithm can be used for rapidly updating previously curated galleries of photos, or curating new galleries, via an appropriately designed Application Programming Interface. Specifically, the API needs to have access to

1. The parameter estimates of the Logit link for the two rates
2. Image processing routines to obtain the color characteristics of photos
3. Text processing routines to process the captions of shared photos
4. Characteristics of the consumers posting the photos
5. Response to the photos in Instagram

The API can then be setup to obtain new photos that appear in social media, process them using the image processing routines, obtain all the associated variables such as the characteristics of the captions and consumers posting the photos, forecast the engagement and exploration rates, and include the photos in a previously posted gallery, or compile new galleries. Additionally, the galleries can be compiled to meet different types of targets based on the priorities of the site. For instance, they can be designed to reach target engagement rates, targeted exploration rates, or targeted engagement and exploration rates. This will automate and vastly decrease the time required to update or setup curated collections of photos. We demonstrate this with a gallery of five photos. We use the model to update this gallery by replacing one of its photos with a photo which the model predicts to have a higher shopping rate and identifies as a possible replacement.

We demonstrate the algorithm with a sample gallery of five pictures in Figure 4. The top row of the figure provides the images in the gallery along with the actual engagement and exploration rates for
the gallery along the left border of the figure. The actual rates are obtained by aggregating the rates for the five images. We then use our algorithm to revise this collection by replacing one of the five images with a different one selected by the algorithm from our sample to increase the engagement rate, exploration rate, or both. Rows 2 – 4 of the figure present the revised galleries along with their aggregate engagement and exploration rates.

Limitations and Future Research

One limitation of our investigation is that we are limited by the data and processing methods in the variables that we include in our investigation. For instance, engagement and exploration rates are likely to also be affected by the emotions displayed in the images. Thus, the response to images that are humorous may be different from those that are not. Similarly, images that are surprising may stimulate curiosity and affect engagement and/or exploration. Developing approaches to rapidly identify and measure the presence and extent of various emotions can significantly improve the curation of galleries.

The effects of the measures that we use to capture the role of visual complexity in response rates are consistent with previous findings. Nonetheless, our measure of visual complexity can be more complete. Specifically, we do not include design aspects of visual complexity (Pieters et al 2010). For instance, the number of objects included in a photo, the extent of their symmetry and similarity and the level of detail in the included objects (Pieters et al 2010) can increase visual complexity and affect response rates.

From a methodological perspective, engagement and exploration rates are likely to be related. Formalizing their inter-dependence and investigating them jointly would not only account for the
dependence between the two rates but can also provide helpful substantive insights regarding, for instance, how much the increase in exploration rates must be for specific increases in engagement rates.
References


MATLAB version 8.2.0701. 2013. The MathWorks Inc.


Twitter (2012), Downloaded from [https://blog.twitter.com/2012/twitter-photos-put-a-filter-on-it](https://blog.twitter.com/2012/twitter-photos-put-a-filter-on-it)


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<th>Median</th>
<th>Max.</th>
<th>Mean</th>
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<td>lo-fi</td>
<td>Dreamy, ever-so-slightly blurry, with saturated yellows and greens</td>
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<td>Nashville</td>
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<td>The Atlantic (2012)</td>
<td>108</td>
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<td>Rise</td>
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<td>infuses a cloudy quality to a photo, almost as if you were daydreaming.</td>
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### Table 3
Summary Measures of Endogeneity Controls

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<th>Median</th>
<th>Max.</th>
<th>Mean</th>
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<td>Caption</td>
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<tr>
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<td>581</td>
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<td>QUEST</td>
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<td>EXCL</td>
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Influence of consumer Posting the Image

| LIKE                      | 0    | 27     | 17100 | 149   |
|                          |      |        |       |       |
| COMMENTS                 | 0    | 2      | 704   | 5.582 |
| FOLLOWERS                | 1    | 611    | 1128000 | 6869  |
| NPHOTOS                  | 2    | 426    | 7233  | 661.1 |

Duration

| DURATION                  | 12   | 65     | 393   | 77.33 |

Number of photos in the gallery

| GALSIZE                   | 5    | 9      | 322   | 14.99 |
Table 4
Comparison of Model Specifications

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<td>MSE (Posterior Mean and 95% Interval)</td>
<td>DIC</td>
<td>MSE (Posterior Mean and 95% Interval)</td>
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<td>0.12 (0.1063,0.137)</td>
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Table 7
Performance Test of the Curation Algorithm

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<th>Engagement Rate (EGR)</th>
<th>Exploration Rate (EXR)</th>
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### Table 5

**Posterior Estimates of the Engagement Rate Model**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Posterior Summary</th>
<th>Variable</th>
<th>Posterior Summary</th>
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<tbody>
<tr>
<td></td>
<td><strong>Mean</strong> 2.50% 97.50%</td>
<td></td>
<td><strong>Mean</strong> 2.50% 97.50%</td>
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<tr>
<td><strong>Color Authenticity</strong></td>
<td></td>
<td><strong>Color Authenticity</strong></td>
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</tr>
<tr>
<td>Red</td>
<td>-0.473 -0.772 -0.166</td>
<td>Amaro*</td>
<td>-0.131 -0.217 -0.042</td>
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<tr>
<td>Chroma of Red*</td>
<td>0.009 0.004 0.014</td>
<td>Hefe</td>
<td>0.016 -0.120 0.150</td>
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<tr>
<td>Lightness of Red</td>
<td>0.001 -0.004 0.006</td>
<td>Hudson</td>
<td>0.008 -0.119 0.134</td>
</tr>
<tr>
<td>Yellow</td>
<td>-0.068 -0.392 0.308</td>
<td>Lo-fi*</td>
<td>0.103 0.011 0.193</td>
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<tr>
<td>Chroma of Yellow</td>
<td>0.001 -0.005 0.006</td>
<td>Mayfair</td>
<td>-0.049 -0.150 0.049</td>
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<tr>
<td>Lightness of Yellow</td>
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<td>Nashville</td>
<td>-0.060 -0.198 0.082</td>
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<tr>
<td>Green</td>
<td>0.637 -0.089 1.357</td>
<td>Rise</td>
<td>-0.024 -0.125 0.076</td>
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<tr>
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<td>sierra*</td>
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<td>Exclamation mark</td>
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<tr>
<td>Coefficient of variation - Chroma</td>
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<tr>
<td>Size in Kilo bytes</td>
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<td>Number of photos in gallery*</td>
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<td>User Photos*</td>
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**Parameters of the Beta Distribution**

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<th>Posterior Summary</th>
<th><strong>Mean</strong> 2.50% 97.50%</th>
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<td>(\alpha^{EGR})</td>
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### Table 6
Posterior Estimates of the Exploration Rate Model

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<td>97.50%</td>
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<td>97.50%</td>
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<td>-0.005</td>
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<td>0.013</td>
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<td>Mayfair</td>
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<td>Coefficient of variation - Chroma</td>
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</tbody>
</table>
Stimuli from social media images collected by firm and curated on its website

Attributes included in our study
- Colors
- Visual Complexity
- Authenticity

Attributes not included in our study
- Number of objects
- Presence of humans
- Emotions of subjects in images
- Image quality

Other stimuli
- Image captions

Website attributes
- Colors
- Content
- Other images
- Promotions

Other factors
- Product Category
- Brand
  - Strength
  - Social media presence
  - Promotional expenditures
- Influence of Consumer Posting the Image
- Visitor Characteristics
- Visit characteristics
  - Time of the day
  - Day of the week
  - Duration of the Image
- Number of photos in the gallery

Figure 1
Conceptual Model
Figure 2
Curated Gallery for the Coach Brand

#COACHFROMABOVE
From New York, from Paris, from Tokyo—from above! Where in the world are you wearing Coach shoes? Tag a photo of them on Instagram, Twitter or Pose with #CoachFromAbove and add your location for a chance to be featured on our map and in our gallery.
Figure 3
Empirical Distributions of Interaction and Shopping Rates

Histogram of Engagement Rate

Histogram of Exploration Rate
Figure 4: Estimated Fixed effects in the Engagement Rate Model
Figure 5: Estimated Fixed effects in the Exploration Rate Model
<table>
<thead>
<tr>
<th>Gallery Type</th>
<th>EGR</th>
<th>EXR</th>
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<tbody>
<tr>
<td>Initial Gallery</td>
<td>0.11</td>
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</tr>
<tr>
<td>Optimized Gallery for EGR and EXR</td>
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<tr>
<td>Optimized Gallery for EGR</td>
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<td>Optimized Gallery for EXR</td>
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