

# The palette that stands out: Color compositions of online curated visual UGC that attracts higher consumer interaction

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**Abstract** Photos posted by consumers on social media, like Instagram, often include brands. Despite the substantial increase in such photos, there have been few investigations into how prospective consumers respond to this *visual UGC*. We begin to address this gap by investigating the role of the color compositions of visual UGC in consumer response. Consumer response is operationalized as the *click-rate* for a photo by a consumer when it is curated on the online site of the brand that it includes. This is the proportion of visitors who click on it for an enlarged view. *Composition* is operationalized as the specific combination of levels of the photo's color attributes: *hue*, *chroma*, and *brightness*. Our goal is to identify the color compositions of photos, *ceteris paribus*, which get more clicks when they are curated. Data for our investigation comes from clicks over a one-year period on photos posted on Instagram curated by fifteen brands in six product categories on their sites. We assume Beta distributed proportions and calibrate a Beta regression using MCMC methods for our investigation.

We find that click-rates are higher for photos that include higher proportions of green and lower proportions of red and cyan. We also find that chroma of red and blue are higher in photos with higher click-rates. Findings from our research led the sponsoring firm to modify its proprietary curation algorithm for client brands. The firm informed us that, post-modification, there has been a substantial increase in click-rates of curated photos for brands in several categories.

**Keywords** Visual UGC · Color composition · Click-rates · Bayesian Beta regression

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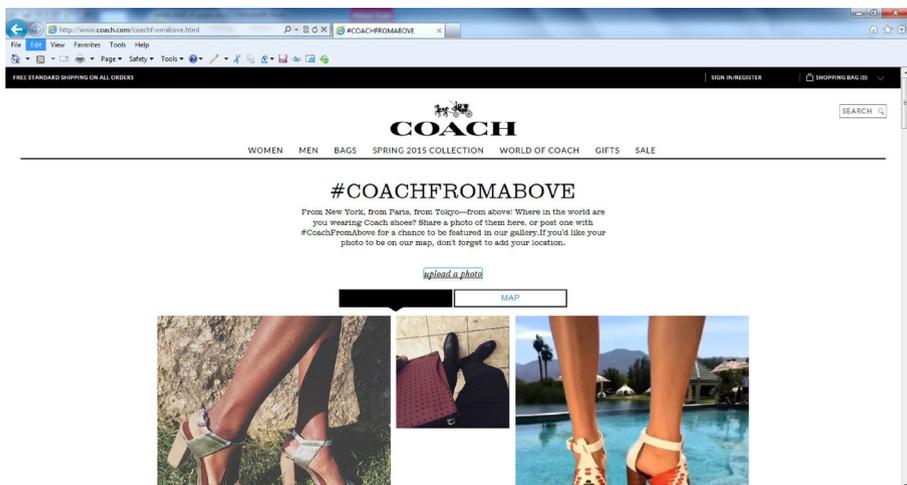
## 1 Introduction

There is an increasing interest in the role of user-generated content like product reviews and ratings in consumer behavior (Berger and Milkman 2012; Chen and Xie 2008; Constant et al. 1996; Shriver et al. 2013; Weiss et al. 2008). Surprisingly, although user-generated content is not always textual, the focus of scholarly research has been almost exclusively on the effect of written reviews and product ratings. Many firms, however, have begun to recognize that user-generated photos on websites like Instagram and Pinterest that show customers using their products affect the behavior of other customers. Some brands have therefore begun to include this visual UGC on their websites (Fig. 1) to stimulate product interest in visitors.

Despite the use by brands and substantial increase in the number of photos posted by consumers (30 billion photos with products have been posted on Pinterest by early 2015 according to the Wall Street Journal (2015)), there have as yet been few investigations into consumer response to visual UGC. This is a surprising gap given longstanding findings in the literature that the visual context in which consumers see products and brands affects how they behave (Wedel and Pieters 2012). In fact, it is more than three decades since Gatignon and Robertson (1985, p.856) first noted the role of visual displays of product-use by consumers on other consumers and its importance as an area of research:

“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.”

The absence of formal insights into consumer response to visual UGC also limits its managerial value. Many websites such as [amazon.com](http://amazon.com), [walmart.com](http://walmart.com), and [yelp.com](http://yelp.com), for instance, present the distribution or average of consumer ratings prominently (Sun 2011) since valence has a stronger influence than volume (Floyd et al. 2014). Such approaches to curating (Brynjolfsson et al. 2013) visual UGC are, however, not yet feasible because very little is known about its role in consumer behavior. This point was also recently made by Yadav and Pavlou (2014) who note that there is a pressing need for formal investigations into visual forms of consumer influence:

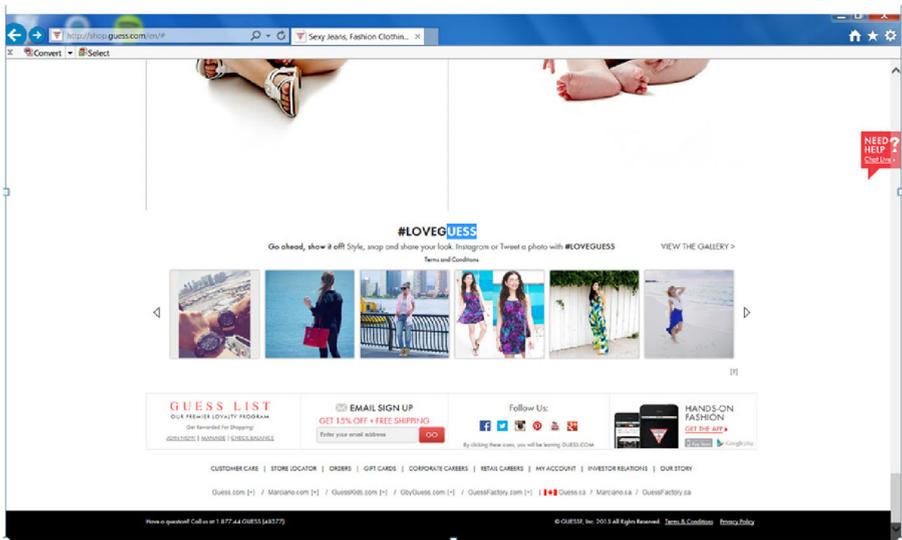


**Fig. 1** Visual UGC posted by [coach.com](http://coach.com)

“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. Despite the increasing interest in curated collections, many questions remain about how they can be monetized or leveraged for marketing purposes.”

Our research attempts to address this gap by developing insights into the role of color compositions in how consumers respond to visual UGC.

Photos can be characterized by several attributes such as visual complexity (Pieters et al. 2010), novelty (Mendelson 2001), aesthetic appeal (Axelsson 2007), picture composition (Walls and Attridge 1977) and color (Meyers-Levy and Peracchio 1992). Color, in fact, is a key attribute of a photo (Axelsson 2007) and color composition has a significant influence on the appeal of any visual presentation (Itten 1960). We therefore investigate how color composition is related to consumer response to visual UGC. Color composition is operationalized as the specific combination of three attributes of color (Gorn et al. 1997): *hue* such as red, green or blue, *chroma* which measures the depth of the hue (e.g., extreme blue vs. light blue), and *brightness* that captures whether a color is bright or dark. Different combinations of hues, chromas, and brightness, would thus lead to different color compositions. The specific goal of our research is to identify the color compositions of photos, ceteris paribus, which get more clicks when they are curated. Data for our investigation comes from visitor response to visual UGC that includes 7631 photos from Instagram across fifteen brands in six product categories over a one-year period. Every photo used in the study includes a product from one of the fifteen brands and is posted by a consumer on the social media site Instagram. Online retail sites of these brands present galleries of photos which include the brands (similar to the one in Fig. 2) to every visitor arriving at their homepages.

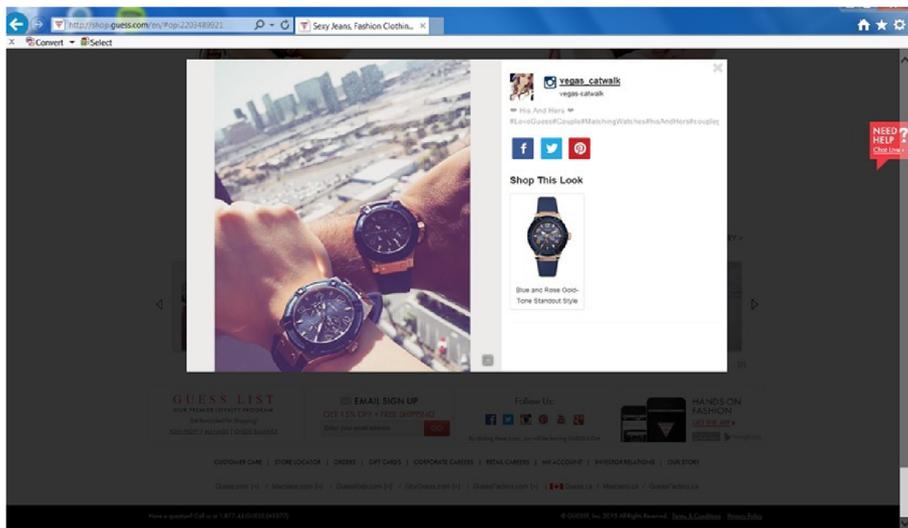


**Fig. 2** Gallery of user-generated photos on [www.guess.com](http://www.guess.com)

The number of times a gallery is presented is recorded as the *number of impressions*. Visitors can click on any photo in the gallery to enlarge it and see a more detailed view of the included product (Fig. 3). We track these clicks and investigate how they vary as the color composition of the photos changes. Thus, the relationship between the color compositions of photos and their *click-rates*, i.e., the number of clicks that a photo attracts as a proportion of the number of impressions, is the focus of our investigation.

Methodologically, we assume that click-rates are Beta distributed (Johnson et al. 1995) and use a Beta regression (Ferrari and Cribari-Neto 2004) for our investigation. Attributes such as visual and design complexity (Pieters et al. 2010), angle of the image (Meyers-Levy and Peracchio 1992), stylistic properties (Peracchio and Meyers-Levy 2005), and the emotional content (Eastwood et al. 2001) of photos can also affect the attention they attract and hence the click-rates. We do not include these attributes in our investigation but rely on the large number of brands, diversity of products, and long duration over which we collect our data, to identify the color compositions associated with higher click-rates. Further, we assume that the roles of color compositions are heterogeneous and randomly distributed across the photos to allow for variations in click-rates resulting from any other factors. We also allow for differences between the product categories and brands via brand fixed-effects and rely on MCMC methods for parameter inference.

Our results suggest that click-rates will be higher for photos whose color compositions include higher proportions of green and lower proportions of red and cyan. We also find that photos with higher click-rates have higher chromas of red and blue. Specific to the features of Instagram, our results also suggest that click-rates are lower for photos that are modified. Specifically, photos



**Fig. 3** Image enlarged in response to a visitor click

whose color compositions were altered using filters in Instagram before being posted have lower click-rates than photos that are not altered.<sup>1</sup>

Previous research has investigated consumer response to color in retail-store environments (Bellizzi et al. 1983; Bellizzi and Hite 1992; Kaltcheva and Weitz 2006), print advertising (Gorn et al. 1997; Meyers-Levy and Peracchio 1995), and branding (Miller and Kahn 2005). Most investigations, however, are in experimental settings and focus on the role of the presence or absence of color (e.g., Meyers-Levy and Peracchio 1995), the effects of specific hues such as red (e.g., Bellizzi et al. 1983), or of specific dimensions of color like chroma (Gorn et al. 1997) on consumer response. Our research, in contrast, is in a field-study setting and makes several contributions to the literature. First, we investigate consumer response to visual UGC which is an issue of increasing importance and has not been formally examined as yet. Second, rather than focusing on specific hues or dimensions of color, we investigate how color compositions are related to consumer response to visual UGC. Since individuals are exposed to colors typically as compositions of several hues and shades rather than specific hues in isolation (Schloss and Palmer 2011), this is a significant distinction of our research. Third, since our investigation is based on tracking customer interactions with visual UGC across several brands and product categories, we are able to provide insights that are not restricted to a specific category or brand.

Since the focus of our research is on the color compositions of visual UGC that attract higher consumer interest, our investigation is at the intersection of three influences on consumers: visual presentation of products, UGC, and colors. We next provide an overview of prior research regarding each of these influences on consumer behavior. We follow this with a description of our data. Following this, we present our empirical model and results. We conclude with managerial implications, a discussion of the results from a field application of our findings, and directions for future research on visual UGC.

## 2 Overview of relevant literature on visual presentations of products, UGC and colors

### 2.1 Visual presentations of products

There are several streams of research on how visual presentations of products influence consumers. The longest and most extensive of these has been on visual merchandising and displays of products in offline retailing (Chandon et al. 2009; Curhan 1974; Chevalier 1975; Gagnon and Osterhaus 1985; Larson et al. 2005; Simonson and Winer 1992; Wilkinson et al. 1982). A consensus finding from these investigations is that how products are presented has a significant effect on consumer response. Lam and Mukherjee (2005), for instance, report that coordinating the visual presentation of clothing items on mannequins in a retail setting to mimic how consumers would use them has a positive effect on purchase intentions.

The visual presentation of products is not restricted to offline retailing but encompasses several other forms of visual communications with consumers (Wedel and

<sup>1</sup> The only exception to this is a filter named Lo-Fi.

Pieters 2007). These include advertising in various media like television, newspapers, magazines, billboards, and online, as well as through product packaging and product demonstrations (Heiman and Muller 1996). The literature has consistently demonstrated the influence of visual communications on consumers' interest in products (Gorn et al. 1997; Wedel and Pieters 2007) and has also investigated how different aspects of such communications play a role in influencing consumers (Pieters et al. 2010). To date, however, there are few investigations of whether consumers respond to visual UGC and, if they do, how the visual characteristics are related to response.

## 2.2 UGC

In contrast to the limited knowledge on visual UGC, there is a rich and growing body of research on textual user-generated content such as product reviews and ratings. The consistent finding from this literature is that user-generated reviews do play a significant role in consumer response in a variety of categories such as books (Chevalier and Mayzlin 2006; Sun 2011), movies (Chintagunta et al. 2010; Duan et al. 2008; Liu 2006), television shows (Godes and Mayzlin 2004), personal care items such as bath, fragrance and beauty products (Moe and Trusov 2011), and video game consoles (Zhu and Zhang 2010).

Chevalier and Mayzlin (2006), for instance, find that reviews by consumers have a significant effect on the sales of books but that negative reviews have substantially larger negative effects on sales than the positive effects of positive reviews. Their results also indicate that, rather than relying solely on summary ratings, consumers also read and use the text of the reviews in arriving at purchase decisions. This finding is replicated in Schlosser (2011) as well who finds that consumers are persuaded more by two-sided reviews than reviews that present only the positive or negative aspects of products. These findings on the importance of content to consumers while using reviews are significant since they suggest that consumers are responsive to detail in user-generated reviews. Thus, colors and color compositions should also play a role in the use of visual UGC by consumers and which visual content they respond to.

Interestingly, despite the extensive research on consumer response to product reviews in various experience goods (Nelson 1970, 1974), the literature has not yet investigated the role of user-generated content in categories such as apparel or shoes where attributes like color, style, and fit play a critical role in consumers' purchase decisions (Alba et al. 1997). This is a significant gap because the ability to assess features such as color and fit "depends on consumers' inferences about the faithfulness of photographic reproduction" (Alba et al. 1997, p. 43) in such categories. Visual UGC may therefore play a significant role in consumers' purchase decisions in these categories. Our research on the characteristics of color compositions of photos that attract consumer clicks thus provides insights in this regard in experience categories such as apparel, cosmetics, jewelry and shoes,<sup>2</sup> where visual presentations of products are important.

## 2.3 Colors

The role of color in consumer response was, in fact, noted over four decades ago (Kotler 1973) and empirically investigated in various contexts. For instance, Bellizzi

<sup>2</sup> These are four of the six categories that we investigate.

et al. (1983) and Bellizzi and Hite (1992) find that the time spent and the number of purchases made is higher in retail stores with more tones of blue in their interiors than those with more tones of red. Additional evidence of the role of colors in consumer response is also reported in the advertising context (Gorn et al. 1997; Meyers-Levy and Peracchio 1995). Gorn et al. (1997), for instance, find that blue elicits more relaxation but not higher likability of the ad or advertised brand. Gorn et al. (1997) also find that higher chroma increases excitement and 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.

One limitation of Gorn et al.'s (1997) research is that they only consider two colors, red and blue, and four chroma and brightness variations of each color and test eight images in all. Their investigation thus does not consider color compositions that include multiple hues or the extensive variations of color compositions with different levels of chroma and brightness that we investigate. This is a significant differentiation of our research from prior literature on how consumers respond to colors in photographs. Some evidence has, in fact, begun to emerge that consumer response to visual messages about products is influenced by color compositions rather than individual colors (De Bock and Van Kerckhove 2014).

Another differentiating aspect of our research is that most investigations of the influence of color on consumer response (Gorn et al. 1997; Hoegg and Alba 2007; Kaltcheva and Weitz 2006; Meyers-Levy and Peracchio 1995; Wedel and Pieters 2014), have been in experimental settings although one exception is the recent work by Bagchi and Cheema (2013).<sup>3</sup> To date, there is no research on how colors and their compositions are related to consumer response to visual UGC as they shop for products.

### 3 Data

We collected our data in collaboration with an agency that searches the social media site Instagram for photos that include products, and supplies them to firms that market those products. Firms that purchase the service post some of the photos on their websites as curated galleries that include smaller versions (1.75" square) of the photos. Visitors to the site can scroll through the galleries to view one or more of the included photos. Each photo also includes a hyperlink to the webpage of the product that it contains. The galleries, however, do not include any price or promotional information for the products in the images.

The agency also installs software on the firms' sites to track the number of visitors and their interaction with the photos. Specifically, for every gallery, the software tracks the specific photos included in the gallery and the number of photos included. Additionally, over the duration that a photo is in a gallery on the website, the software also tracks the total number of visitors who were exposed to the photo, i.e., the number of impressions it received, and the number of visitors who clicked on it to enlarge it.<sup>4</sup>

We collect our data by tracking the impressions and clicks for visual UGC posted on the websites of fifteen firms across six product categories including

<sup>3</sup> Nonetheless, these authors as well consider only two hues, red and blue, but neither their variations nor compositions with other hues.

<sup>4</sup> Visitors to the sites do not see the number of other visitors who clicked on a photo. Click-rates are therefore uninfluenced by social effects (Chen et al. 2011).

apparel, clothing, cosmetics, jewelry, news, and shoes. Between these firms, the prices of the marketed products ranged from \$6.00 to \$1300. Some of the firms also had highly diverse product mixes. One firm, for instance, had products with prices between \$50 and \$1300. Visitors to the websites with the posted photos are therefore likely to be diverse both within and across firms. The diversity reduces the likelihood of systematic correlation between the three color variables, hue, chroma, and brightness, that we investigate and other variables such as website characteristics, product prices, or individual visitor characteristics, that we do not include in our analysis.

The staff in the marketing departments of the firms selected the photos, from those posted by their customers on the social media site Instagram, for inclusion in galleries on their sites. The selection was based on the staff's subjective judgments of the photos' likely appeal to visitors to the sites. A key advantage of this approach, for our investigation, is that every firm's staff is likely to select photos that they believe would stimulate the interest of website visitors in the firm's products. Differences between the photos posted on a brand's site in click-rates are therefore unlikely to be due to systematic differences between them in how well they present the products that they include.

The diversity of product categories and brands also reduces the likely effects of the subjective selections of the photos by the staffs of the firms. Specifically, neither the brand logos nor the products of the fifteen firms were similar in terms of their color compositions. It is, therefore, unlikely that the staff across all fifteen firms would be systematically biased towards certain colors in the posted photos.

The presentation of visual UGC in the form of galleries where a photo has to be clicked to see an enlarged view provides an additional advantage in our investigation. Specifically, each photo in the gallery is about 1.75" square in size. Since each of the photos is quite small when first presented, details of the objects in the photos are unlikely to be clearly visible (for example, as in the case of the leftmost photo in the gallery in Fig. 2). Recent research (Wedel and Pieters 2014) suggests that, under such "blurred" conditions, "the color composition" of the photos plays a significant role in consumers' comprehension of their content. Thus, the click-rates of the photos in our investigations are more likely to be due to the color compositions than their contents.

Finally, the galleries are always presented at the bottom of the screen and designed so as to include about six photos at a time (the galleries can be scrolled to the right or left to view additional photos). Rather than reacting to a single ad or photo at a time, as is typical in previous research on consumer response to colors in photos (Pieters et al. 2010), visitors to the websites in our research therefore view multiple photos simultaneously. Thus, each presentation of a gallery is in a setting where the other photos in the gallery serve as a control group for each photo.

We collected our data over a period of more than one year from August 29th, 2012, through September 13th 2013. Since our data spans a period of more than a year, our findings are not subject to temporal effects like seasonality (Anderson and Simester 2014) in investigations of consumer response to user-generated content. Over this period, the firms displayed 7631 photos in all. We selected a sample of 5541 photos (about 75% of the sample) for calibrating our model and used the remaining 2090 for predictive testing.

## 4 Variables

### 4.1 Click-rate

The variable of primary interest for our research is the click-rate for each photo in our sample. Formally, the rate is defined as:

$$Y_{ijk} = \frac{C_{ijk}}{N_{ijk}} \quad (1)$$

$Y_{ijk}$  = click-rate for photo  $i$  of gallery  $j$  on the site of brand  $k$  during the period that the photo was on the site,  $C_{ijk}$  = number of visitors who clicked on the photo during the period that the photo was on the site, and  $N_{ijk}$  = number of impressions, i.e., the number visitors who saw photo  $i$  of gallery  $j$  on the site of brand  $k$  during the period that the photo was on the site.

### 4.2 Colors

A digital photo is a mosaic of millions of pixels (Blinn 2005). Each pixel is encoded with information on hue which is the color carried by the pixel, chroma which is the depth of the hue in the pixel with higher values corresponding to greater depth, and brightness which represents how bright or dark the hue is (Othman and Martinez 2008). For each photo in our sample, we use MATLAB's Image Processing Toolbox (MATLAB 2013) to obtain the three measures in the CIE-Lch color-space (Kuehni 2003) across six hues, red, yellow, green, cyan, blue, and violet. This is a significant departure from previous research on color in marketing (Bagchi and Cheema 2013; Bellizzi and Hite 1992; Gorn et al. 1997) where typically only a few colors like blue and red are investigated.

For each photo  $i$ , of gallery  $j$ , on the site of brand  $k$ , we compute the following eighteen variables: (1)  $P_{H,ijk}$  = Proportion of all the pixels that carry hue  $H$ ,  $H$  = red, yellow, green, cyan, blue, violet;  $0 \leq P_{H,ijk} \leq 1$  (2)  $C_{H,ijk}$  = mean chroma of the pixels that carry hue  $H$ ;  $0 \leq C_{H,ijk} \leq 100$  with higher values indicating higher depth of the hue (3)  $B_{H,ijk}$  = mean brightness of the pixels that carry hue  $H$ ;  $0 \leq B_{H,ijk} \leq 100$  with higher values indicating higher brightness.

### 4.3 Variations in colors

Variations of chroma and brightness of hues can affect how viewers respond to photos (Pieters et al. 2010; Putrevu et al. 2004). We therefore compute two variables to capture these variations in each photo:  $CVC_{ijk}$ , the coefficient of variation of chroma across all the pixels in the photo and  $CVB_{ijk}$  which is the coefficient of variation of brightness across all the pixels in the photo. Table 1 gives the distribution of colors and their variations for the photos in our sample.

### 4.4 Filters

Before a user posts a photo, Instagram gives the option of changing its appearance by modifying its color composition using several filters. Since we compute the color variables from the posted photos, the color attributes in our data take such alterations into account. Any alteration of colors using filters, however, will "change the way that the scene looks

**Table 1** Distribution of color characteristics of photos in the sample

	Min.	Median	Max.	Mean
$P_{Red}$	0	0.20	0.99	0.24
$C_{Red}$	0	20.76	93.34	22.41
$B_{Red}$	0	44.98	98.44	45.20
$P_{Yellow}$	0	0.23	0.99	0.26
$C_{Yellow}$	0	15.46	85.26	17.13
$B_{Yellow}$	0	73.66	99.46	70.15
$P_{Green}$	0	0.02	0.98	0.04
$C_{Green}$	0	6.13	76.99	8.29
$B_{Green}$	0	64.60	99.73	60.62
$P_{Cyan}$	0	0.01	0.94	0.03
$C_{Cyan}$	0	5.57	45.17	7.58
$B_{Cyan}$	0	61.06	99.92	57.20
$P_{Blue}$	0	0.06	0.99	0.12
$C_{Blue}$	0	8.70	78.97	11.41
$B_{Blue}$	0	34.49	99.59	36.40
$CVC$	0.05	0.67	3.82	0.73
$CVB$	0.06	0.53	5.31	0.56

in a photograph” (London et al. 2011, p. 84). Since our color variables cannot capture such changes, we include indicator variables for filters to capture their effects.

Although Instagram offers more than twenty filters, not all are used by consumers. We select the ten most used filters and combine the other filters into an ‘other’ category. Unfortunately, Instagram does not provide verbal or pictorial definitions of most of the filters in the application. Figure 4 resents a collage of filtered versions of the photo in Fig. 3 filtered with each of the ten filters used in our investigation.

If a photo in the sample was modified using a filter before it was posted, we set an indicator variable for that filter to 1. Thus, we use 11 indicator variables,  $A_N$ ,  $N = 1, 11$ , in all to represent filters. Zeroes across all 11 variables for a photo therefore indicate that it was not altered before it was posted on Instagram. For each of the eleven types of filters, Table 2 presents the number of photos in the calibration sample that were modified with that filter.

#### 4.5 Number of photos in the gallery

Regardless of how many photos are included, only about six can be presented at a time to visitors. Additional photos can be brought into view by visitors if they scroll through the gallery. Thus, photos in galleries that include more than six photos may receive a different number of impressions than those that contain only six unless visitors choose to scroll. To account for such variations between galleries, we rely on a variable,  $NGAL$ , which is the number of total photos in the gallery in which the photo is included.



Fig. 4 Effects of the filters

### 4.6 Exploratory analysis

The goal of our research is to investigate if and how color compositions affect response to visual UGC. We therefore first perform a simple descriptive analysis to assess whether, prima facie, our data provides evidence of the role of color compositions in click-rates. Specifically, we compare the click-rates under four broad scenarios where the first scenario

Table 2 Definitions and distribution of filters

Filter	Frequency in Sample
Amaro	333
Hefe	132
Hudson	141
lo-fi	304
Mayfair	231
Nashville	108
Rise	200
sierra	99
Valencia	496
x-pro ii	274
Other	425
Photos with no filters	3209

corresponds to compositions of colors where all six hues are about even in their presence in the photos and no hue dominates. In the second scenario, each of the six hues, in turn, would have a larger share of the colors in the photo and thus have a dominant presence. We refer to the first scenario as the Control Scenario and each of the other six as Treatment – Hue Dominant. Thus, we have six treatment categories: (1) Treatment – Red Dominant (2) Treatment – Yellow Dominant (3) Treatment – Green Dominant (4) Treatment – Cyan Dominant (5) Treatment – Blue Dominant and (6) Treatment – Violet Dominant. In Scenario 3, we divide the photos in each Treatment – Hue Dominant condition into four quartiles based on the levels of the hue’s chroma in the photos assigned to the condition and repeat this in Scenario 4 based on the levels of the hue’s brightness in the photos.

We operationalize the Control Scenario as a composition where each of the six hues is present in (0%, 20%] of all the pixels in the photo. Each of the Treatment – Hue Dominant scenarios is operationalized as a composition where the dominant hue has between (20%, 40%] of the pixels in the photo. Next, we draw photos from our dataset that correspond to each of the seven conditions and compute the average click-rates of the photos in the sample (the total number of photos in each condition would therefore be different). Table 3 presents the number of photos in each condition and the mean click-rate for that condition along with a sample photo from each. The mean click-rates suggest that the composition of the photo does play a role. Thus, for instance, all of the Hue-Dominant scenarios with the exception of Green and Blue have lower mean click-rates than the Control Scenario. The Cyan, Violet and Red Dominant conditions have the three lowest mean click-rates while that of Blue and Green have the two largest mean click-rates both of which are higher than that for the Control Condition. Similarly, the click-rates for photos in the upper quartiles of chroma and brightness for Green are substantially higher while those for Cyan are substantially lower than the control condition. These summaries, overall, thus suggest that color compositions may play a role in consumer response.

## 5 Model

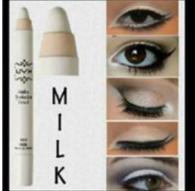
Since our response variable is a proportion, we assume that it follows the Beta distribution (Johnson et al. 1995). As suggested by Ferrari and Cribari-Neto (2004), and transform the distribution into a form in which the mean can be related to explanatory variables. Formally, we assume that the click-rate  $Y_{ijk}$  for photo  $i$ , in gallery  $j$ , of brand  $k$ , is distributed as

$$f(Y_{ijk}) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} Y_{ijk}^{\mu\phi-1} (1-Y_{ijk})^{(1-\mu)\phi-1}, 0 < Y_{ijk} < 1 \quad (2)$$

$$E(Y_{ijk}) = \mu \quad (3)$$

$$V(Y_{ijk}) = \frac{\mu(1-\mu)}{(1+\phi)} \quad (4)$$

**Table 3** Exploratory analysis

Condition	Number of photos	Mean click-rate	Sample photo	Chroma (top quartile)	Brightness (top quartile)
Control	84	0.539		NA	
Yellow	182	0.538		0.559	0.565
Cyan	14	0.490		0.530	0.360
Violet	50	0.502		0.416	0.571
Red	129	0.525		0.566	0.537

**Table 3** (continued)

Condition	Number of photos	Mean click-rate	Sample photo	Chroma (top quartile)	Brightness (top quartile)
Green	42	0.566		0.768	0.648
Blue	97	0.577		0.548	0.494

### 6 Link

For each photo, we relate the mean of the click-rate distribution,  $\mu$ , to its color attributes, whether it had a filter applied to it, and the number of photos in the gallery in which it was included. Specifically, following Ferrari and Cribari-Neto (2004) we use a Logit link to model the click-rate as follows:

$$\text{Logit}(\mu_{ijk}) = \sum_H \beta_{P_H} \cdot P_{H,ijk} + \sum_H \beta_{C_H} \cdot C_{H,ijk} + \sum_H \beta_{B_H} \cdot B_{H,ijk} + \beta_{CVC} \cdot CVC_{ijk} + \beta_{CVB} \cdot CVB_{ijk} + \sum_{N=1,11} \beta_{A_N} \cdot A_{N,ijk} + \beta_N \cdot \log(NGAL_{ijk}) + \gamma_k + \delta_{jk} \tag{5}$$

$H = \text{red, yellow, green, cyan, blue}$ ,<sup>5</sup>  $A_{N,ijk} = 1$  if filter  $N$  is used for the photo, 0 otherwise;  $N = 1, \dots, 11$ ,  $\gamma_k = \text{fixed effect of brand } k$ .  $\delta_{jk}$  assumed to be  $N(0, \tau_\delta)$  is the random effect of gallery  $j$  of brand  $k$ .  $\delta_{jk}$  is included to account for potential effects of specific combinations of photos in a gallery. For instance, a gallery that includes photos which contain a specific combination of filters may elicit different responses from visitors to the photos than galleries that contain other combinations.

Whether a photo evokes a response from visitors is also likely to be affected by several other attributes such as visual complexity (Pieters et al. 2010), angle of the image (Meyers-Levy and Peracchio 1992), stylistic properties (Peracchio and Meyers-Levy 2005), and emotional content (Eastwood et al. 2001). Although we do not explicitly include such factors in our link, we rely on the large number of brands, diversity of products, and long duration over which we collect our data to reduce the likelihood of

<sup>5</sup> Since the inclusion of all six hues in the specification results in collinearity, we only include five of the six hues and drop violet from the model.

biased estimates of the roles of color attributes. It is unlikely, for instance, that specific types of visual complexity or specific angles of images occur systematically with the same color compositions. Similarly, specific stylistic properties such as orientations of the photos are unlikely to be correlated with specific color compositions. We also assume that the parameters in (5) are randomly distributed across the photos in our sample. To the extent that the omitted variables are not correlated with the included ones, the random coefficients formulation controls for the effects of the omitted variables by letting the parameters vary from the mean. We therefore assume  $N(0, 10)$  priors on all the parameters in the link and uninformative Gamma priors on the parameters,  $\phi$  and  $\tau_\delta$ .

### 7 Empirical analysis

We estimate our model using MCMC methods and take the following approach. We begin with a specification of the link using only the brand fixed-effects and gallery random-effects but no predictor variables in the specification. This version serves as our baseline specification, S0:

$$\text{Logit}(\mu_{ijk}) = \gamma_k + \delta_{jk} \tag{6}$$

We then include the variables for the hues to assess the effects of the colors but not of their chroma or brightness and obtain specification S1 of the link:

$$\text{Logit}(\mu_{ijk}) = \sum_H \beta_{P_H} \cdot P_{H,ijk} + \gamma_k + \delta_{jk} \tag{7}$$

The addition of the chroma and brightness variables completes the inclusion of all color composition characteristics and leads to specification S2:

$$\text{Logit}(\mu_{ijk}) = \sum_H \beta_{P_H} \cdot P_{H,ijk} + \sum_H \beta_{C_H} \cdot C_{H,ijk} + \sum_H \beta_{B_H} \cdot B_{H,ijk} + \gamma_k + \delta_{jk} \tag{8}$$

A comparison of the explanation provided by S1 relative to S0, in terms of a model fit measure like the Deviance Information Criterion, or the accuracy in predicting the click-rates in the holdout sample, will provide insights into whether the hues in the photos can explain the variations in click-rates. Comparing the DIC's of S2 and S1, on the other hand, reveals whether chroma and brightness are also associated with click-rates while a comparison of S2 and S0 would answer the question of whether color compositions can explain variations in click-rates between photos.

Specification S3 includes the two variables for color variations and helps us understand whether overall variations in chroma and brightness, regardless of specific hues that they occur in, can also explain click-rates:

$$\text{Logit}(\mu_{ijk}) = \sum_H \beta_{P_H} \cdot P_{H,ijk} + \sum_H \beta_{C_H} \cdot C_{H,ijk} + \sum_H \beta_{B_H} \cdot B_{H,ijk} + \beta_{CVC} \cdot CVC_{ijk} + \beta_{CVL} \cdot CVL_{ijk} + \gamma_k + \delta_{jk} \tag{9}$$

We next formulate specification S4 by including the variables for the filters to assess whether the changes that they make to how photos look (London et al. 2011) are also related to click-rates<sup>6</sup>:

$$\text{Logit}(\mu_{ijk}) = \beta_{P_H} \cdot P_{H,ijk} + \sum_H \beta_C \cdot C_{H,ijk} + \sum_H \beta_{B_H} \cdot B_{H,ijk} + \sum_{N=1,11} \beta_{A_N} \cdot A_{N,ijk} + \gamma_k + \delta_{jk} \tag{10}$$

The final specification, S5, includes the number of photos in the gallery that each photo is included in:

$$\text{Logit}(\mu_{ijk}) = \sum_H \beta_{P_H} \cdot P_{H,ijk} + \sum_H \beta_{C_H} \cdot C_{H,ijk} + \sum_H \beta_{B_H} \cdot B_{H,ijk} + \sum_{N=1,11} \beta_{A_N} \cdot A_{N,ijk} + \beta_N \cdot \log(NGAL_{ijk}) + \gamma_k + \delta_{jk} \tag{11}$$

## 8 Results

### 8.1 Can the color compositions of photos explain the differences in click-rates between photos used as visual UGC on retail websites?

Table 4 presents the DIC and predictive performance - operationalized as the mean squared error in predicting the click-rates for each photo in the prediction sample - of each of the five specifications. The entries in the table show a distinct pattern of larger improvements in DIC and predictive performance with the addition of some variables than others. The variables that lead to larger improvements than other variables are hues, chroma and brightness, and filters. Thus, these comparisons clearly demonstrate that color compositions have a significant association with click-rates. An additional finding from these comparisons is that click-rates also vary with filters. Overall, however, the table clearly demonstrates that the addition of color composition variables, i.e., the color, chroma and brightness attributes of photos, results in the largest improvement in predictive performance.<sup>7</sup>

### 8.2 Characteristics of color compositions of photos in visual UGC that receive higher click-rates

Table 5 gives the posterior means and credible intervals of the parameters of specification S5. Of the five hues, red and cyan have significant negative estimates while green has a positive estimate. This is consistent with previous findings in the literature (Bellizzi et al. 1983) that red is seen as more negative and stressful and reduces exploration while green generates positive feelings such as “cool” and “welcoming” and increases exploration and time spent in retail stores by consumers. Recent findings

<sup>6</sup> The DIC’s of specifications S1-S3 suggested that the coefficients of variation of chroma and brightness do not affect click-rates. We therefore dropped them from S4.

<sup>7</sup> Since it only includes brand fixed-effects and gallery random effects, predictions using specification S0 are the same as a heuristic based on the assumption that, conditional on being shown, every photo in a gallery has the same probability of being clicked by a visitor.

in social psychology (Lichtenfeld et al. 2012) also suggest that viewing green tones stimulates creativity and exploration.

One finding that is interesting and has not been previously reported in the literature is the large negative estimate of cyan. Cyan, in fact, has the largest of the three significant estimates for hues on click-rates. This is a new and important result in our investigation since the role of cyan in consumer behavior has not been explored previously. Our results suggest that it can be detrimental to consumer response to visual UGC.

Two of the other variables that represent color compositions – chroma of red and blue – have significant positive estimates on click-rates. Thus, photos with higher click-rates also have a higher depth of these hues. These effects are consistent with earlier findings. For instance, Valdez and Mehrabian (1994) report that increases in chroma are arousing and Gorn et al. (1997) find that increases in chroma lead to greater excitement for advertisements.

The negative effects of the three filters Amaro, Sierra and Valencia, are consistent with the estimated effects of the hue and chroma variables. Amaro enhances aqua (The Atlantic 2012) which is a form of cyan while Sierra and Valencia soften photos<sup>8</sup> (Mashable 2012; The Atlantic 2012) thus reducing the chromas of the hues. Lo-Fi, on the other hand, increases the chroma of green (The Atlantic 2012). Since green has a positive effect on click-rates, higher chromas of green could be related to further increases in click-rates.

Figure 5 gives a box plot of the posterior distributions of the estimated fixed effects of the fifteen brands. The category of the brand and the number of observations in the sample corresponding to the brand are along the left border of the plot. The effects vary across the brands indicating that visual UGC posted at some brands' sites receives higher click-rates than that posted by other brands. The variation of fixed-effects also suggests that the effects of the brands on click-rates are being captured and are not biasing the estimates of the color compositions.

Overall, therefore, our results suggest that color compositions of visual UGC with higher click-rates will have low levels of red and cyan, high levels of green, and high chromas of red and blue. Additionally, photos modified by filters that increase the level of cyan or reduce chromas will have lower click-rates while those that have higher chromas or the level of green should be higher. An additional insight from the estimate of the number of photos in the gallery is that photos in larger galleries will have higher click-rates than those in smaller ones.

### 8.3 Investigation of an alternative explanation

An alternative explanation for our findings could be that consumers visiting a brand's site are primed (Herr 1986, 1989; McNamara 1992) by the colors in the brand's logo and as a result develop a preference for visual UGC that has those colors. This is the implication of Mandel and Johnson's (2002) findings that when individuals are primed by an attribute related to a product, and are subsequently exposed to different product options, they will prefer the option that includes the primed attribute. This would mean

<sup>8</sup> Unfortunately, Instagram does not provide verbal or pictorial definitions of most of the filters in the application. We therefore relied on definitions in the media.

**Table 4** Comparison of specifications

Specification	Predictors included	DIC	MSE of holdout sample
S0	None	-5150	0.06013
S1	Hues	-5180	0.06003
S2	Hues, chroma and brightness	-5199	0.05992
S3	Hues, chroma, brightness, variations of chroma and brightness	-5199	0.05988
S4	Hues, chroma, brightness, filters	-5221	0.05980
S5	Hues, chroma, brightness, filters, number of photos in the gallery	-5223	0.05827

that the higher click-rates realized by photos at any brand's websites would have more of the hues in that brand's logo. For this to be systematically the case, however, the visual UGC at the websites of the brands in our study should include photos that have more of the colors in the brand's logos.

To investigate this alternative explanation, we compute the levels of the five hues included in the logos of each of the fifteen brands that we investigate and check whether there is a systematic relationship between the hues in the brands' logos and the average levels of the hues in the visual UGC posted on the brands' websites. Hue-wise scatterplots of the average proportion of the hue in the visual UGC posted in the galleries of each brand's website and the proportion of the same hue in the brand's logo are presented in Fig. 6. Clearly, there is no systematic relationship between the average level of any of the hues in the photos and those hues' levels in the brand's logo.<sup>9</sup>

## 9 Managerial implications and implementation of findings

### 9.1 Three questions

Our findings raise two important questions for practice: (1) What does the color composition of low proportions of red and cyan, high proportion of green, and high chromas of red and green, recommended by our findings translate into in terms of specific values? (2) What proportions of hue and levels of chroma are low and what levels would be high? We address these questions next.

The negative estimates of red and cyan imply that photos which have either of the hues in them should not be used as visual UGC. Similarly, the positive estimate of green means that photos which mostly or exclusively have the hue should be used. It may, however, be infeasible to follow either of the implications in practice. For instance, red is one of the three basic hues and is widely used in brand logos (Labrecque and Milne 2013), packaging (Labrecque and Milne 2012) and product

<sup>9</sup> For each photo in our sample, we defined a new indicator variable set to 1 if the dominant hue in the photo – in terms of its proportion being higher than that of all other hues – is the same as the dominant hue in the logo of the brand for the product in the photo. When we recalibrated the specification S5 with this indicator variable added as a covariate, the estimates and the model's fit did not change and, consistent with this, the parameter for the indicator variable was not significant.

**Table 5** Parameter estimates

Variable	Posterior summary		
	Mean	2.50%	97.50%
<b>Colors</b>			
Red <sup>a</sup>	-0.237	-0.396	-0.079
Chroma of Red <sup>a</sup>	0.004	0.002	0.006
Brightness of Red	0.000	-0.002	0.001
Yellow	0.060	-0.088	0.207
Chroma of Yellow	-0.002	-0.005	0.000
Brightness of Yellow	-0.001	-0.002	0.000
Green <sup>a</sup>	0.490	0.177	0.796
Chroma of Green	-0.002	-0.005	0.001
Brightness of Green	0.000	-0.001	0.001
Cyan <sup>a</sup>	-0.737	-1.076	-0.388
Chroma of Cyan	0.002	-0.002	0.005
Brightness of Cyan	-0.001	-0.002	0.000
Blue	-0.126	-0.309	0.054
Chroma of Blue <sup>a</sup>	0.003	0.000	0.005
Brightness of Blue	0.000	-0.002	0.001
<b>Filters</b>			
Amaro <sup>a</sup>	-0.136	-0.221	-0.052
Hefe	0.039	-0.092	0.175
Hudson	0.082	-0.049	0.211
lo-fi <sup>a</sup>	0.134	0.045	0.221
Mayfair	-0.064	-0.169	0.042
Nashville	-0.094	-0.242	0.051
Rise	-0.008	-0.113	0.099
sierra <sup>a</sup>	-0.242	-0.383	-0.102
Valencia <sup>a</sup>	-0.087	-0.158	-0.013
x-pro ii	0.035	-0.061	0.131
Other	0.022	-0.055	0.100
Number of photos in gallery <sup>a</sup>	0.139	0.088	0.195
Precision of Gallery random effects <sup>a</sup>	11.110	8.863	13.820
Precision of the Beta Distribution <sup>a</sup>	8.669	8.346	9.006

<sup>a</sup> 95% posterior credible interval does not include zero

coloration to convey quality (Keller 1993; Rouillet and Droulers 2005). Similarly, few products or contexts in which products are used are entirely green and many categories such as apparel have products that include multiple hues.

Our findings should therefore be interpreted as identifying the relative levels of hues and chromas in the composition of the photos and implemented accordingly. Thus, for instance, if a brand's logo is predominantly red as in the case of the retail firm Target, user-generated photos that include the brand's logo and some green-colored content

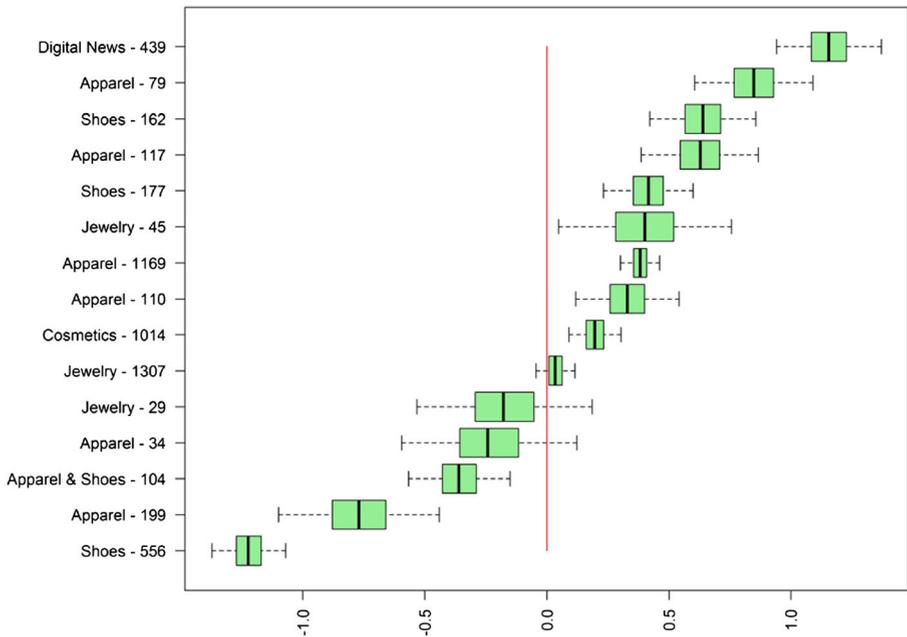


Fig. 5 Fixed effects of brands

(Fig. 7) should be given precedence, over those that include the logo and additional red-colored content (Fig. 8), when visual UGC is curated on the firm’s website. Further, given the positive effects of chromas of red, green, and blue, user-generated photos with higher chroma values of all three hues (Fig. 9) should be preferred over those that include only high chroma of red (Fig. 10) since consumer response to visual

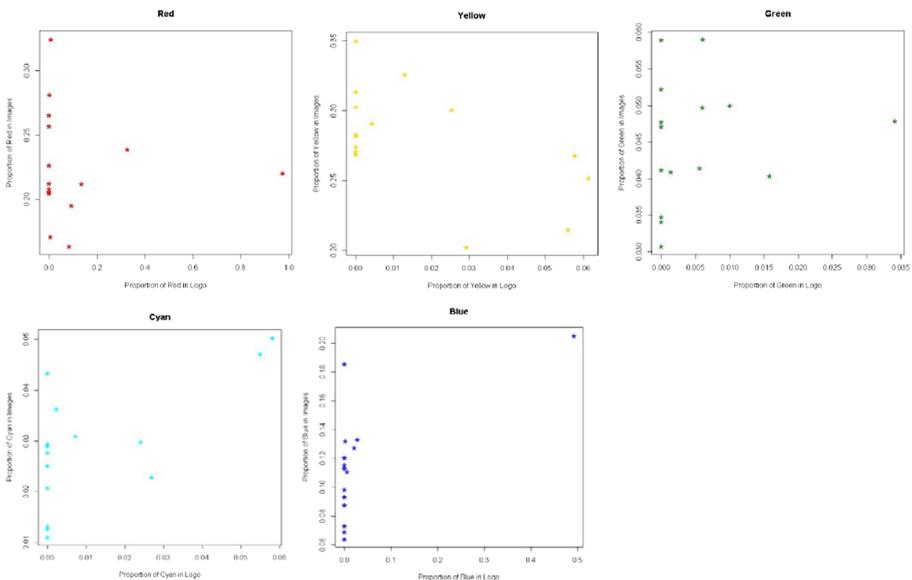


Fig. 6 Levels of hues in brand logos and visual UGC

communications is stronger for compositions of colors than individual hues (De Bock and Van Kerckhove 2014).

Given the large number of visual UGC on social media sites like Instagram and Pinterest, visual inspection and selection as above of user-generated photos may not be feasible. The selection process can, however, be automated by relying on software like Matlab that we use in this research to analyze photos and select only those that have preferable compositions, i.e., with higher proportion of green than red or cyan and high chromas of red, green and blue.

A third question that we address is related to curation. What do our findings mean in terms of how photos are presented in terms of their order from left to right and which photos go next to each other? Our findings also provide some insights into how the selected photos can be curated in the form of galleries. Once user-generated photos for inclusion on a brand's site are selected, those that have compositions that are likely to receive higher click-rates than others in the selected set, should be given precedence in the gallery. Specifically, they should be the photos that should be visible without visitors having to scroll through the gallery. Further, since pictures are typically viewed in the same direction in which text is read, i.e., from left to right usually (Walls 1959, p. 315), the leftmost photo in the gallery should have the composition that is predicted to attract the largest click-rate, the next one the next largest, and so on.

## 9.2 Implementation of findings

The sponsoring agency first started as a business to locate and provide photos posted on Instagram to firms if their brands are included in the photos. Subsequently, however, the agency's management decided to offer curation services as well but had few insights into how photos should be selected for curation and what photo-characteristics were influential in visitors' response. They therefore started by selecting photos randomly from the visual UGC that they collected for brands but did not see significant increases in consumer response to the products in the curated galleries. Our research, thus, provided the first insights to them that color compositions of photos are important drivers of consumer response and led to a decision to use the hues, chromas,

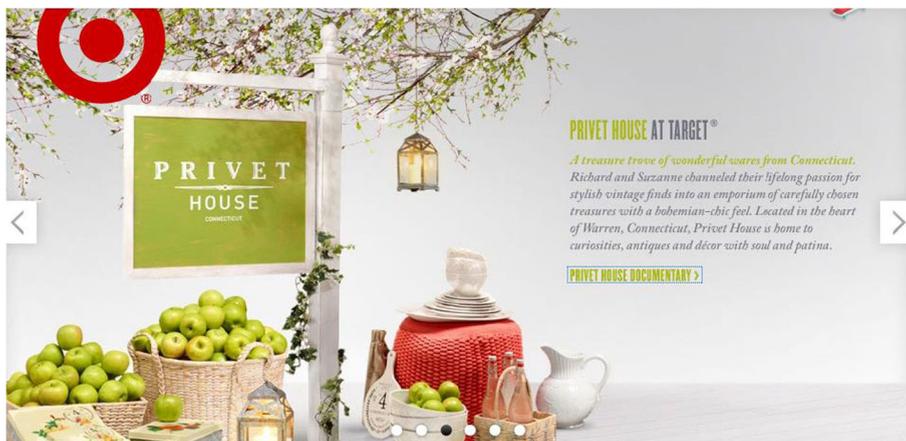


Fig. 7 Visual UGC for target with red and green



**Fig. 8** Visual UGC for target with only *red*

and brightness, of photos, and any filters used on them, as variables in the selection process. They, therefore, decided to develop algorithms internally relying on commercially available machine-learning packages which typically use approaches like regression trees, random forests, and gradient boosting (Lemmens and Croux 2006). The packages were trained to identify the hues, chroma, brightness, and filters in photos that can enhance click-rates for different client brands. The resulting algorithms were then used to curate visual UGC on client sites.

### 9.3 Improvements in click-rates

Due to competitive reasons, the agency was unable to provide the click-rates for their client brands with random selection of photos and with their algorithms. They, however, informed us that the inclusion of the color composition variables in their machine learning algorithms led to substantial improvements in performance over random selection. Since we were unable to obtain details of the extent of improvement in the agency's results due to our research, we took the following approach to estimate the



**Fig. 9** Visual UGC of a target store's interior with high chromas of *red*, *green* and *blue*



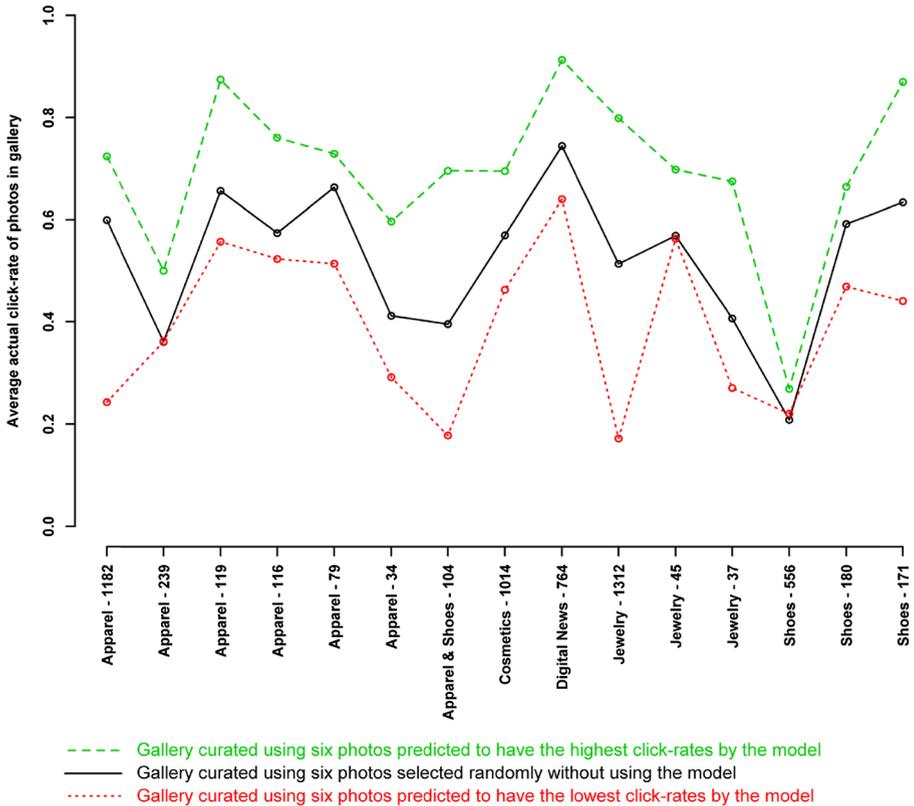
**Fig. 10** Visual UGC of the Target store in Fig. 9 with high chroma of red

same. For each brand that we used in our empirical investigation, we used the click-rates predicted by our model and scored the photos of each brand in our dataset in descending order. We then used three approaches to select six of these photos to hypothetically curate a gallery of visual UGC for each brand and obtain click-rates for the gallery (we selected six photos since visitors to online retail sites are typically presented with six photos before they can scroll through to other photos in the gallery).

In the first approach, we selected the top-scored six photos and used the average of their actual, observed, click-rates (which are recorded in our data) as the average for the gallery. For our second approach, we selected the lowest-scored six photos and used the average of their actual, observed, click-rates (which are, again, recorded in our data) as the gallery click-rate. The click-rate from the lowest-scored photos serves as the worst-case scenario if, per chance, the agency were to pick the worst possible photos for curation. Finally, in the third approach we mimicked the random approach used by the agency prior to our research. Specifically, we considered the entire set of each brand's photos in our dataset, assumed that each photo in the set had an equal chance of being selected, selected six photos randomly, and obtained the average of their observed click-rates. We repeated this random selection a thousand times for each brand and used the mean of the average click-rates from the thousand iterations as the average click-rate for the gallery if photos were to be selected randomly.

If indeed our findings helped the sponsoring agency improve the curation process, the click-rates of galleries curated with the top-scored photos should be higher than those of the random approach. The random approach, however, should perform better than the gallery with the six lowest-scored photos since managers at the agency should be able to rely on their brand experience and avoid worst-performing photos.

Figure 11 presents the click-rates from the three approaches for all 15 brands in our data organized by product category and by the number of photos of each brand within each product category. Each point on the x-axis represents one of the 15 brands in our data and the associated legend gives the category of the brand and the number of photos in the sample for the brand. It is clear from this figure that our model would have helped the agency improve the click-rates of the curated galleries above the random-selection process that they had followed previously. The improvement in fact is



**Fig. 11** Actual click-rates of galleries curated using model-based scoring and random selection

substantial for several brands and, importantly, does not demonstrate any systematic relationship with product categories or the number of photos available in our dataset for the brands.

The figure also provides another interesting and important insight. Specifically, the solid line corresponding to the random selection of photos is representative of the average click-rates that each brand would have gotten if our model was not used. It, thus, represents the fixed-effects of brands on click-rates. The click-rates corresponding to the dashed line, on the other hand, represent the improvements due to the selection of the best photos for each brand by our model. The fact that the selected photos indeed have higher observed click-rates is a clear indication that scoring by our model can identify photos that are likely to have the highest click-rates. Similarly, the actual click-rates corresponding to the dotted line are lower than those for the solid line indicating again that scoring by our model can identify photos that are likely to have the lowest click-rates. Since our model only includes variables related to color compositions of the photos and brand fixed-effects for scoring, its consistency in identifying photos that will have the highest and lowest click-rates across all fifteen brands and seven product categories provides additional evidence that our findings would have indeed improved the sponsoring agency's curation approaches and the click-rates of the curated visual UGC.

## 9.4 Improvements in business outcomes

The agency provided us measures of improvement in business outcomes after galleries of Instagram photos chosen by their algorithms were curated at the online sites of client brands in multiple categories. The measures were collected over a one-month period with the goal of comparing the performance of the sites before and after the galleries were curated based on their algorithms. The specific outcome tracked varied across clients based on their business priorities at the time of the test. In all, four outcomes were tracked across the sites:

1. Conversion Ratio: percent of the visitors who buy a product after visiting its page
2. Average Order Value: average of the amount spent on products purchased at the site
3. Sales: total volume of sales during the period
4. Retargeting Click-through Rate: Online retailers use retargeting (Lambrecht and Tucker 2013) to advertise their products to visitors who came to their sites previously as the visitors browse other websites. One of the agency's clients was interested in understanding how retargeting ads that included Instagram photos recommended by the agency's algorithm would perform relative to those that used subjectively selected photos. The measure of performance that the client was interested in was the percent of retargeted visitors who would click the ad and return to the site.

Table 6 presents the results of the test for seven clients in six categories. It's clear from the table that the changes in the agency's approach to curation of visual UGC, based on our descriptive findings, led to improved results on all four outcomes for all the tested brands and categories. The improvements in conversion ratio are particularly high in retail. Additionally, there is a large increase in retargeting click-through rates as well. The improvements, in fact, are substantial in some cases.

## 10 Conclusions, contributions, and future research directions

Visual UGC is one form of personal visual influence of consumers on other consumers. Despite three decades since the call by Gatignon and Robertson (1985) for research into its role, and the enormous growth in images posted by consumers on social media such as Instagram and Facebook, visual UGC has not yet attracted much attention from marketing scholars. As suggested by Yadav and Pavlou (2014) recently, there is therefore a pressing need for formal investigations of how visual UGC influences consumer behavior. This is the issue that we address in this research by investigating how color composition is related to consumer response to visual UGC. Our specific focus is on the proportion of visitors to retail websites that click on user-generated photos to enlarge and see them in greater detail.

Our investigation is based on data collected by tracking for over one year the click-rates of visitors to the online retail sites of fifteen brands in six product categories that post visual UGC. Specifically, we track click-rates for 7631 photos each of which includes a product and is posted by a consumer on

**Table 6** Field implementation results

Category	Increase in Conversion Ratio	Increase in Average Order Value	Increase in Revenue	Increase in click through rate in Facebook retargeting ads
Clothing	60%		\$700,000	
Jewelry, accessories and gifts - Client 1	42%	23%		
Jewelry, accessories and gifts - Client 2	9%	7%	\$155,000	
Mass Merchandise	73%			
Discount Retail	110%			
Bicycles and accessories	80%	\$50		
Furniture and Home Goods				43%

the social media site Instagram. Our results identify the characteristics of color compositions of visual UGC with higher click-rates as lower proportions of red and cyan, a higher proportion of green, and higher chromas of red, green and blue. A field implementation of machine learning algorithms trained based on these patterns in two categories included in the study (Apparel and Jewelry) and two that were not (Department Stores and Discount Retail) led to substantial increases in click-rates for visual UGC relative to the practice of selecting posted photos subjectively. Additionally, using the algorithms to select photos to be included in ads displayed on the social media site Facebook also resulted in significant increases in click- rates for the ads.

### 10.1 Substantive contributions

The primary substantive contributions of our research are in developing insights into two issues: (1) how online retail consumers respond to visual UGC and (2) the role of color compositions i.e., hues, chroma, brightness, and variations of chroma and brightness. To our knowledge, there is no past work on whether and how visual UGC influences consumers in online retail settings. We therefore believe that our investigation of these questions on multiple brands and product categories is a significant substantive contribution to the literature.

With regard to our second contribution, while there is some past research on consumer response to color, the focus has been on the effects of specific aspects of color rather than on the holistic effects of color compositions. We provide below two examples of how past research on consumer response focused on specific aspects of color.

1. Differences between blue and red: In this stream, the focus is on the effects of specific hues (e.g., red vs. blue) on consumer response. For instance, Bellizzi et al. (1983) and Bellizzi and Hite (1992) find that the time spent and the number of purchases made is higher in retail stores with more tones of blue in their interiors than those with more tones of red.

2. Effects of high and low chroma or brightness: The focus here is on the effects of specific properties of colors like chroma and brightness on consumer response. Gorn et al. (1997), for instance, find that higher chroma increases excitement and 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.

Our findings, however, demonstrate that consumers respond to color compositions rather than to specific hues or specific levels of chroma or brightness by themselves. We believe that this is a significant contribution of our research since it alerts both scholars and practitioners to the importance of considering the effects of color compositions of visual stimuli as a whole, and not just those of specific aspects of colors, on consumers.

## 10.2 Limitations and future research directions

A key limitation of our study is that it was not conducted in a controlled experimental setting. Further, despite the fact that our findings resulted in modifications of the sponsoring agency's curation algorithms, we did not have access to the details of the algorithms or detailed results of the implementation. Our findings cannot, therefore, be viewed as causal effects of color compositions on consumer response to visual UGC. A very useful direction for future research, therefore, is experimental investigations of whether there are causal relationships between color compositions and consumer response to visual UGC.

Two other limitations of our study are that we only focus on click-rates and do not investigate the effects of color compositions on purchases of products included in visual UGC. Further, all the categories in our study are experience goods although consumers post visual UGC for search goods like computers and consumer electronics as well. An additional limitation is that selection of photos by the marketing staff could play a role in visitor response to the curated galleries. In addition to these three limitations as possible directions for future research, we see several additional opportunities for extending our work.

First, there is a need to investigate the role of other factors such as the interactions of visual and design complexity (Pieters et al. 2010) with color compositions on consumer response to visual UGC. Second, consumers often include themselves in photos that they post. Their presence, the emotions that they express, and their demographics such as age and gender may also play a role and interact with the influence of color compositions. Third, consumers may be quite heterogeneous in their photographic skills and how they present themselves and products in photos that they post. How this heterogeneity affects visitor response to the photos when they are posted on retail sites is an important issue for additional research. Fourth, photos may differ in the duration for which they are relevant. This may be the case particularly in fashion categories. An investigation of the roles that color compositions and other attributes of photos play in how long a photo is able to attract visitor interest would be a fruitful avenue of research and can provide insights into how often sites need to change the visual

UGC that they post. Finally, it would be useful to investigate how the role of color compositions varies with the type of product displayed in the photo. Advances in vision recognition and computer science (e.g., Flickner et al. 1995) could be useful in this regard in identifying specific products in visual UGC.

Two other critical issues are related to the design of galleries. Specifically, there is a need for investigations of the order of placement of photos in the galleries, i.e., which photos should be at the ends and serve as anchors and which should be in the middle when they are presented. Additionally, how response rates differ between galleries that are organized vertically and need visitors to scroll from top to bottom and those that are scrolled from left to right needs formal investigations as well.

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## Appendix

### Cobb-Douglas Formulation of the Model

In response to a referee's concern that, "our additively separable specification" of the Logit link in our model does not truly capture the effects of color compositions, we estimated the model using the following Cobb-Douglas type of specification of the link:

$$\text{Logit}(\mu_{ijk}) = \prod_{H, j=1,6} P_{H,ijk}^{(\beta_{PH} + \beta_{CH} \cdot C_{H,ijk} + \beta_{BH} \cdot B_{H,ijk})} + \sum_{N=1,11} \beta_{AN} \cdot A_{N,ijk} + \beta_N \cdot \log(NGAL_{ijk}) + \gamma_k + \delta_{jk}$$

This specification allows all aspects of each hue's proportion, chroma, and brightness, to affect the role of the other hues as in a typical Cobb-Douglas formulation. We calibrated this model as well using MCMC methods and present the results in Appendix Table 7. A comparison of the significant effects from the two specifications suggests that:

1. Hues: The direction of the effects of red, green, and cyan hues is unchanged – both red and cyan continue to have a negative effect while green has a positive effect.
2. Chromas: The chromas of red and blue continue to have a positive effect.
3. Additional insights: One advantage of the Cobb-Douglas formulation is that it permits us to include all the colors rather than relying on Violet as the base. We therefore find that violet also has a positive effect on click-rates. Additionally, this specification indicates that the brightness of cyan has a small positive effect.

Thus, while the findings from the additively-separable specification remain essentially unchanged, we obtain additional insights from the new specification. We would like to thank the anonymous reviewer for raising the issue prompting us to investigate the alternative specification.

**Table 7** Parameter estimates of cobb-douglass specification

Variable	Posterior Summary		
	Mean	2.50%	97.50%
Colors			
Red <sup>a</sup>	-0.056	-0.086	-0.024
Chroma of Red <sup>a</sup>	0.001	0.000	0.002
Brightness of Red	0.000	-0.001	0.001
Yellow	0.016	-0.038	0.055
Chroma of Yellow	0.000	-0.001	0.001
Brightness of Yellow	0.000	-0.001	0.000
Green <sup>a</sup>	0.046	0.011	0.086
Chroma of Green	0.001	-0.001	0.002
Brightness of Green	-0.001	-0.001	0.000
Cyan <sup>a</sup>	-0.036	-0.060	-0.009
Chroma of Cyan	-0.002	-0.003	0.000
Brightness of Cyan <sup>a</sup>	0.001	0.000	0.001
Blue	-0.018	-0.040	0.004
Chroma of Blue <sup>a</sup>	0.001	0.000	0.002
Brightness of Blue	0.000	0.000	0.000
Violet <sup>a</sup>	0.050	0.025	0.075
Chroma of Violet	-0.001	-0.002	0.000
Brightness of Violet	-0.001	-0.001	0.000
Filters			
Amaro	-0.148	-0.239	-0.057
Hefe	0.047	-0.092	0.174
Hudson	0.051	-0.087	0.177
lo-fi	0.140	0.045	0.229
Mayfair	-0.072	-0.166	0.027
Nashville	-0.025	-0.169	0.126
Rise	0.003	-0.103	0.111
sierra	-0.222	-0.368	-0.071
Valencia	-0.096	-0.174	-0.022
x-pro ii	0.052	-0.042	0.149
Other	0.030	-0.047	0.107
Number of photos in gallery	0.112	0.058	0.167
Precision of Gallery random effects <sup>a</sup>	8.639	8.319	8.931
Precision of the Beta Distribution <sup>a</sup>	11.480	8.999	14.300

<sup>a</sup> 95% posterior credible interval does not include zero

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