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RESEARCH NOTE

A Computer Vision Methodology to Predict Brand Personality from Image Features

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ABSTRACT
Using the computer vision method, this study proposes an analytical model of visual aesthetics for brand communication and analyzes the effects of visual features (i.e., colors and visual complexity) on brand personality. This study illustrates a four-step procedure correlating computationally coded visual attributes with human ratings of perceived brand personality. This study has important methodological implications for advertising researchers and practitioners.

Companies are searching for ways to create a distinctive and meaningful brand image. The construct of brand personality emerged as a key concept that attributes symbolic meanings to a brand by associating it with human characteristics (Aaker 1997). A prominent way to build brand personality is through manipulating a brand's visual identity, such as logo, colors, and packaging (Pringle and Binet 2005; Eisend and Stokburger-Sauer 2013). Psychologically, visual aesthetics attract attention, convey specific meanings, evoke emotions, and stimulate consumers' memories, thoughts, and experiences (Elliot 2015). The prevalence of visual-based social media platforms, such as Instagram and Snapchat, opens opportunities for brands to build an even stronger visual identity with a richer graphic conversation via images and videos (Bashir et al. 2018).

Color psychology theory suggests that colors connote various meanings and uniquely shape brand perceptions (Labrecque 2020). For example, red expresses brand excitement and passion (Labrecque and Milne 2012); yellow implies cheerfulness and happiness that links to brand sincerity; and blue relates to trustworthiness and security, reflecting brand competence (Grohmann, Giese, and Parkman 2013). Compared with brand logos and product packaging, branded images on social media are more visually complex, composed of multiple colors and different visual elements (e.g., edges). Visual complexity significantly influences perceived brand personality (Bajaj and Bond 2018). Thus, this study integrates literature on color psychology and visual complexity and proposes an analytical model to study visual aesthetics for brand communication using computer vision methods (see Figure 1).

While colors and visual complexity have been proven to be powerful predictors of brand personality from respective literature groups, no comprehensive framework has examined the combined effects of colors and visual complexity owing to methodological limitations. Existing studies mainly used experimental methods and only examined the effects of a particular visual dimension (e.g., saturation, feature complexity, the color red) or compared a limited set of visual attributes (e.g., red versus blue). Unlike traditional visual analysis that depends on human coders' manually annotating a limited sample of images, computer vision allows researchers to calculate visual attributes from given images

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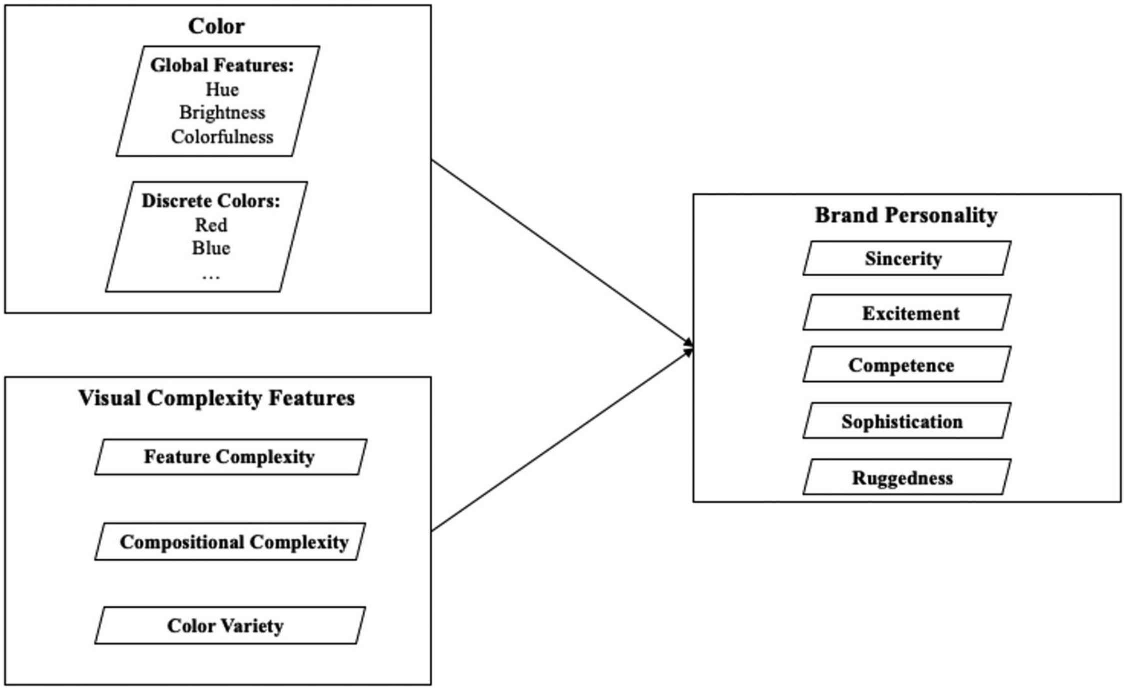

Figure 1. An analytical model of studying visual aesthetics for brand communication. Hue may be used to refer to different colors as well (e.g., red, blue). When used in a color model, it is typically expressed quantitatively as a single numerical value (also see Figure 4).

automatically (Ha et al. 2021). Empowered by computer vision methods, this study systematically tests the effects of a large set of relevant visual features on brand personality and extends our current piecemeal understanding of visual feature effects. Methodologically, this exploratory study aims to contextualize computer vision methods in advertising research.

Literature Review

Brand Personality

Brand personality has been associated with the metaphor of "brand as a person," endowing the brand with human personality traits (Aaker 1997). The brand personality dimension includes sincerity, excitement, competence, sophistication, and ruggedness (Aaker 1997). Sincerity is typified by traits such as wholesome, down to earth, and honest. Excitement refers to traits such as daring, imaginative, and exciting. Competence is characterized by traits such as intelligent, secure, and confident. Sophistication is typified by traits such as glamorous, smooth, and charming. Ruggedness is characterized by traits such as strong, masculine, and outdoorsy.

Analytical Model for Studying Visual Aesthetics for Brand Communication

This analytical model explicates two main visual aesthetics aspects: colors and complexity. Both influence consumers' perceptions of brand personality significantly but have not been examined together in one study setting. In the following sections, we explain why each visual feature in the proposed model is relevant to brand personality.

Hue Color

Each color is typically represented in three dimensions: hue, brightness, and saturation. Hue is the perceptual attribute corresponding to a color's dominant wavelength in the visible electromagnetic spectrum, representing the specific type of color, such as red, orange, and blue. Previous consumer research has consistently demonstrated strong associations between colors and personality traits. Initial work on brand personality by Aaker, Fournier, and Brasel (2004) used different colors to manipulate the perceived personality of an online service brand. For example, individuals characterize blue hues with competence, trustworthiness, security, and sincerity; red hues with imagination and excitement; yellow and orange with sincerity, excitement, and refreshment; black hues with sophistication; and green and brown hues with ruggedness (Grohmann, Giese, and Parkman 2013). Furthermore, Labrecque and Milne (2012) suggested that exposure to a brand's visual identity (e.g., a blue brand logo) triggers intrinsic generic hue-related color meaning in memory (e.g., blue is competent),

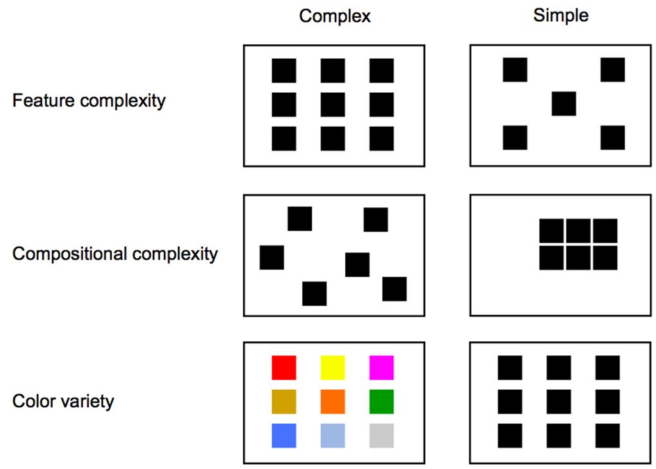

Figure 2. Visual illustration for the three dimensions of visual complexity.

contributing to the perceptions of brand personality (e.g., a brand with a blue logo is competent). Therefore, this study further explores the role of color hue in influencing brand personality when consumers are exposed to brand visuals on social media.

> **RQ1:** What color(s) are associated with the perceived **(a)** sincerity, **(b)** excitement, **(c)** competence, **(d)** sophistication, and **(e)** ruggedness?

Brightness

Brightness refers to the perception of luminance. As a continuous dimension, a higher score in brightness denotes a color appearing as more "whitish," like white mixed into a pigment. In contrast, a color low in brightness appears "darkish," like black mixed into a pigment. Golden and Zimmerman (1986) found out that low-brightness colors are associated with an upscale image and tend to be adopted by prestigious stores; in contrast, high brightness is related to a discount-store image. Moreover, low-brightness colors may increase the perception of the ruggedness dimension in brand personality, because lower brightness can be linked to the feeling of being unrestricted and in control (Labrecque and Milne 2012). In contrast, higher brightness has been found to lessen the arousing effect of certain hues (e.g., red) by inducing a calming effect (Profusek and Rainey 1987), which may suggest a negative relationship with brand excitement (Labrecque and Milne 2012).

> **RQ2:** How is brightness related to perceived **(a)** sincerity, **(b)** excitement, **(c)** competence, **(d)** sophistication, and **(e)** ruggedness?

Colorfulness

The concept of colorfulness was developed based on human perceptions (Hasler and Süsstrunk 2003). Greater colorfulness indicates more pigment than colors with lower colorfulness; such high-colorful colors are rich, vivid, and striking, while low-colorfulness colors are perceived as dull (Gorn et al. 1997). Similar to brightness, previous research failed to consider colorfulness when examining color effects. Colorfulness increases arousal (Valdez and Mehrabian 1994; Hagtvedt and Adam Brasel 2017) and may be positively associated with brand excitement and ruggedness (Labrecque and Milne 2012).

> **RQ3:** How is colorfulness related to perceived **(a)** sincerity, **(b)** excitement, **(c)** competence, **(d)** sophistication, and **(e)** ruggedness?

Visual Complexity

Defined as the number of elements in an image and the detail of information these elements deliver (Deng and Poole 2010), visual complexity is conceptualized as two dimensions: feature and compositional complexities (Pieters, Wedel, and Batra 2010; Donato and Adigüzel 2022). Feature complexity reflects the density and number of perceptual features in an image (Lazard and Mackert 2014), which denote the amount of material and heterogeneity of elements (Berlyne and Peckham 1966). Compositional complexity refers to the spatial distribution of visual elements in an image (Mai et al. 2014), indicating irregular arrangement (Pieters, Wedel, and Batra 2010). Given that this study examines the combined effects of colors and visual complexity using computer vision methods, color variety is included as the third dimension of visual complexity (see Figure 2, Peng and Jemmott 2018). Color variety indicates the variety of colors used in an image (Purchase, Freeman, and Hamer 2012), which reflects the dissimilarity of visual elements and the number of details in an image (Pieters, Wedel, and Batra 2010).

Literature on visual processing and aesthetics demonstrates that visual complexity significantly influences perceived brand personality because the presence and arrangement of design elements may affect brand impressions. First, building on Berlyne's (1974) aesthetic theory, recent branding and marketing research has found that complex visual patterns trigger uncertainty in consumers, resulting in heightened arousal, which further bolsters perceptions of brands as exciting (e.g., Bajaj and Bond 2018; Nicholls 2021). The positive relationship between visual complexity and experienced arousal manifested through self-report arousal measures (Bajaj and Bond 2018) and psychophysiological responses (Tuch et al. 2009). Luffarelli, Stamatogiannakis, and Yang (2019) further showed that the visual asymmetry effect, which operates through a congruency of arousal and asymmetry, increases consumer evaluations of brand excitement in logo design.

Second, the value of symmetry in artistic and visual design has been proven to enhance perceptions of aesthetic pleasure (Reber, Schwarz, and Winkielman 2004). Extending this logic to brand imagery, Bajaj and Bond (2014) demonstrated that less visually complex elements (i.e., symmetrical design) bolstered the perceptions of brand sophistication by triggering impressions of aesthetic quality. Similarly, when studying social media posts of luxury brands, Lee, Hur, and Watkins (2018) revealed that less complex images led consumers to perceive that brands have a high luxury value, closely reflecting brand sophistication.

Moreover, contrary to aesthetic product value, Creusen, Veryzer, and Schoormans (2010) suggested that visually complex products were attractive to consumers who attached more importance to utilitarian value; complex-looking product designs would look more technologically complex and infer more functionalities. Furthermore, King, Lazard, and White (2020) showed that increased visual complexity encouraged users to perceive online information as more useful and visually informative. These attributes (i.e., functionality, usefulness, and informativeness) closely represent brand competence.

Previous research also found that simpler designs were associated with product attributes of reliability, authenticity, and sobriety, which closely reflect the sincerity dimensions of brand personality (Favier, Celhay, and Pantin-Sohier 2019; Nicholls 2021). Moreover, increased visual complexity led to greater perceived brand ruggedness, evoking perceptions of toughness, strength, and the outdoors. As mentioned, social media images are often visually complex because they may be composed of various objects, spatial arrangements, and colors, influencing consumers' perceptions of brand personality. Therefore, we propose the following three research questions to explore the effects of visual complexity.

RQ4: How is feature complexity related to perceived **(a)** sincerity, **(b)** excitement, **(c)** competence, **(d)** sophistication, and **(e)** ruggedness?

RQ5: How is compositional complexity related to perceived **(a)** sincerity, **(b)** excitement, **(c)** competence, **(d)** sophistication, and **(e)** ruggedness?

RQ6: How is color variety related to perceived **(a)** sincerity, **(b)** excitement, **(c)** competence, **(d)** sophistication, and **(e)** ruggedness?

Method

To examine the effects of visual features on consumers' perceived brand personality, we propose a four-step procedure (see Figure 3) that integrates computer vision methods and traditional survey data.

Step 1: Data Retrieval and Cleaning

Before retrieving imagery data, we identified the focal product category: lifestyle brands. Many lifestyle brands, like fashion and beauty, were identified as top performers on Instagram (Shepherd 2022). These brands embody their own aspirations consistently through products and visual presentations on social media (Saviolo and Marazza 2012), often adopting aesthetic visuals to communicate brand identity (Kim and Brandon 2010). Second, we selected seven lifestyle brands (e.g., ASOS, H&M) based on an industry report identifying them as high performers on social media (Rise Pro 2019; see Supplemental Online Appendix 1 for details). After choosing the brands, we used Instagram-scraper, a command-line application in Python (https://github.com/rarcega/instagram-scraper), to retrieve the most recent 200 Instagram posts (from the date of August 19, 2019) from each account. Other media types, such as videos and stories, were removed from the data set. We randomly selected 100 images from each brand account. The final sample included 700 images, with 100 from each brand.

Step 2.1: Computer Vision Analysis

In this stage, we explained in detail the calculation of each visual feature. The Python package Athec (https://github.com/yilangpeng/athec) was utilized to

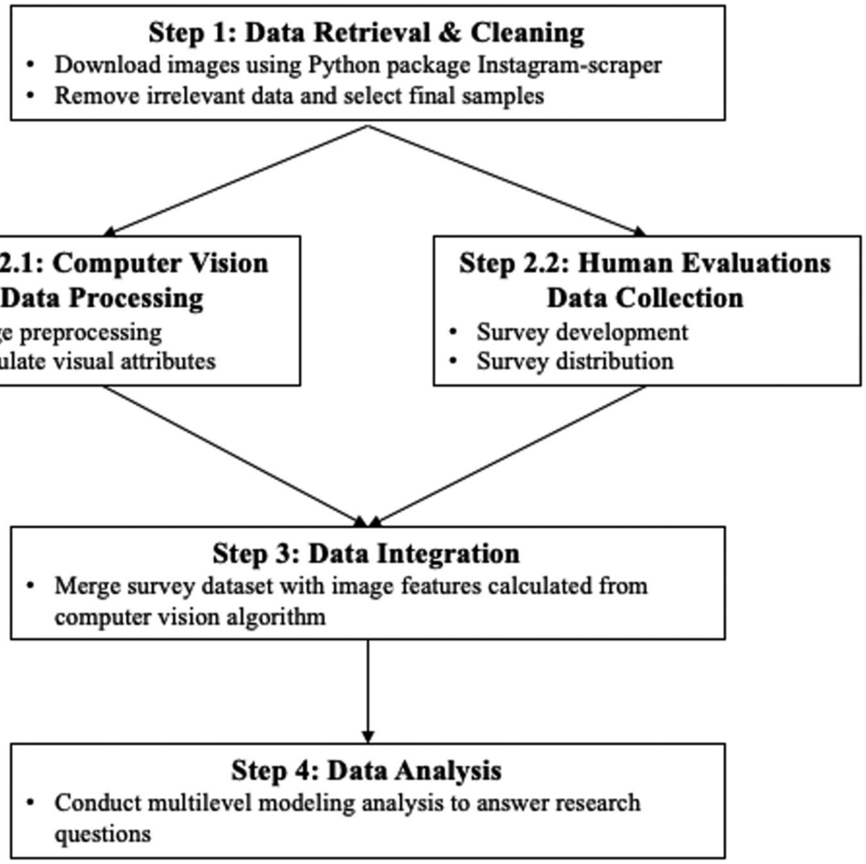

Figure 3. Computer vision research method procedure.

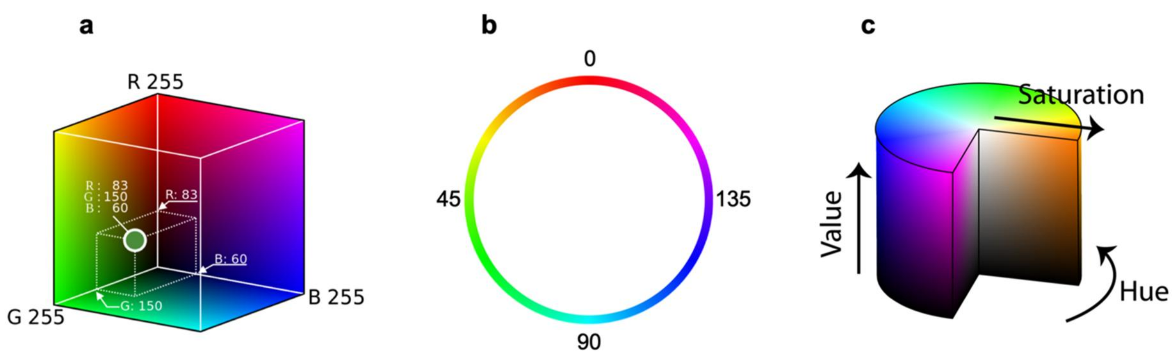

Figure 4. Different color models. (a) In the RGB color space, a color is represented as the combination of red, green, and blue values; (b) hue is represented as a circular spectrum; (c) in the HSV color space, a color is represented as the combination of hue, saturation, and value. Credits: (a) from Horst Frank, (c) from SharkD.

extract visual features in this article. The code is made publicly available on GitHub to help advertising researchers implement similar analyses in other contexts. Please refer to Peng (2021) for a detailed introduction to the package.

Step 2.1a: Preprocessing

Images retrieved online often differ in formats and sizes. We first converted all the images into JPG format and resized them to similar sizes.

Step 2.1b: Calculating Visual Aesthetics

An image is commonly stored in a computer as a matrix of pixels. Each pixel is the smallest unit in an image, storing color information regarding a specific location. In grayscale images, a pixel is stored as a single digit, often ranging from 0 (black) to 255 (white), indicating varying shades of gray. In color images, a pixel comprises a collection of numbers, most often three, representing a specific color.

To replicate colors in digital images, several color models are available. This study primarily relied on two models: RGB and HSV (Figure 4). In an RGB color space, a color is determined as the combination of red (R), green (G), and blue (B) values, each ranging from 0 to 255. In an HSV color space, a color is determined as the combination of hue (H), saturation (S), and value (V). Hue defines the specific kind of color (e.g., red, orange, blue) and is represented as a circular spectrum number from 0 to 180, with 0 representing red and gradually transitioning to orange, yellow, green, blue, purple, and returning to red.

Next, we describe how to calculate color-related features.

Color Percentages

We used a database from van de Weijer, Schmid, and Verbeek (2009), which split the entire RGB color space into 32,768 bins (eight bins per channel) and matched each bin into one of the 11 basic colors (i.e., red, orange, yellow, green, blue, pink, purple, brown, black, white, and gray). With this data set, we categorized each pixel's RGB values and calculated the percentages of 11 colors in the image (Figure 5). Given that the percentages of two achromatic colors (black and white) had already been conceptually reflected by brightness and colorfulness, we excluded them from the analysis.

Colorfulness

The saturation channel in the HSV color model reflects the chromatic intensity of color. Nevertheless, such a measure is designed to help computers represent colors of a simple patch and may not fully reflect human perceptions of colorfulness in an image (Hasler and Süsstrunk 2003). Alternative measures have been developed that align more with human perceptions. Our study used the colorfulness metric proposed by Hasler and Süsstrunk (2003), which has been shown to align better with human perception. Their validation study obtained a correlation of 0.953 with human ratings of colorfulness. This measure also correlates better with crowdsourced workers' perceptions of colorfulness than saturation (Sharma and Peng 2023). Based on the RGB model, we first computed two additional channels:

$$rg = R - G$$
$$yb = \frac{(R+G)}{2} - B$$

Then, an image's colorfulness (C) can be computed with the following formula; μ and σ stand for mean and standard deviation, respectively.

$$C = \sigma_{rgyb} + 0.3\mu_{rgyb}$$
$$\sigma_{rgyb} = \sqrt{\sigma_{rg}^2 + \sigma_{yb}^2}$$
$$\mu_{rgyb} = \sqrt{\mu_{rg}^2 + \mu_{yb}^2}$$

Hue

In the HSV color space, we averaged the hue values of all the pixels in the image. In general, a higher hue value means the overall tone of the image is more bluish than reddish (Reece and Danforth 2017).

Brightness

In the HSV color space, V represents the brightness of the color. We used the average value in the HSV color space of all the pixels to represent this attribute.

The second set of visual features pertains to the three dimensions of visual complexity: feature complexity, composition complexity, and color variety (see Figure 6).

c

black	2%
blue	6%
brown	21%
gray	5%
green	19%
orange	3%
pink	19%
purple	1%
red	9%
white	5%
yellow	11%

Figure 5. The calculation of different color percentages: (a) original image; (b) color categorization; (c) percentages of different colors.

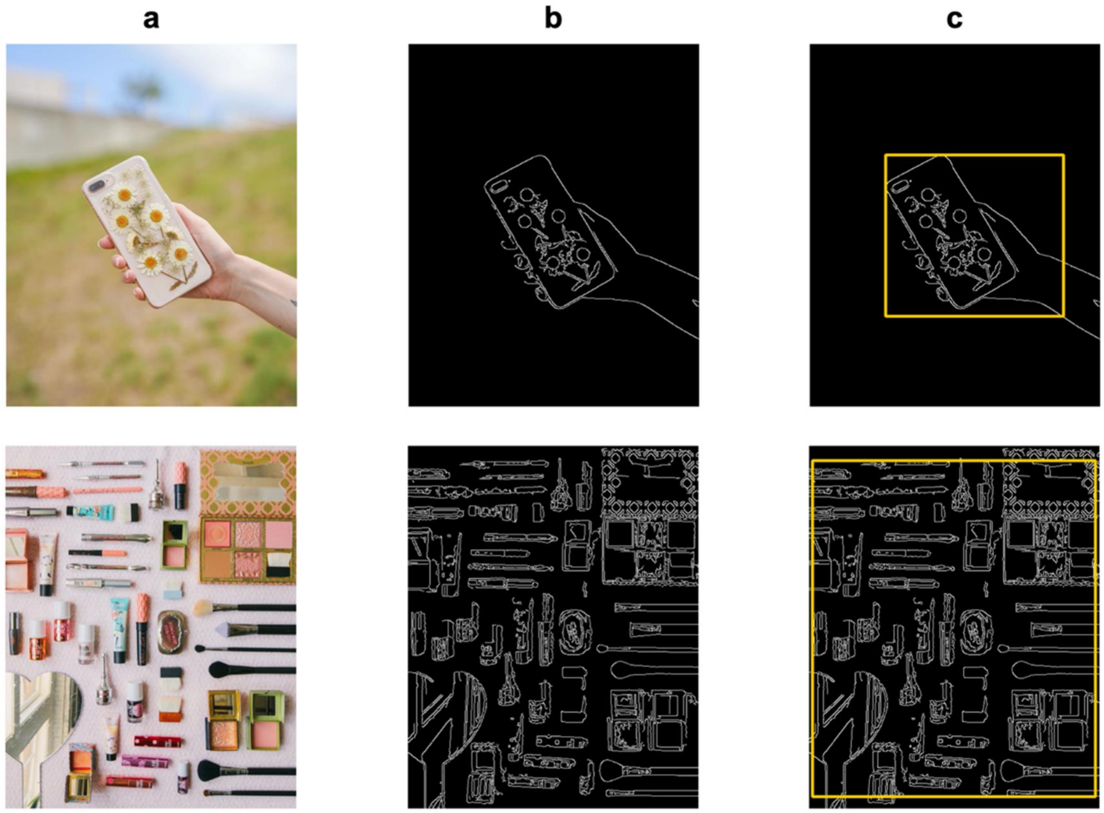

Figure 6. The calculation of visual complexity: (a) original image; (b) edge detection; (c) a bounding box that contains 90% of the edge points. A simple image (top panel) has few edge points and a smaller bounding box than a complex image (bottom panel).

Feature Complexity

We used two measures: the JPG file size and the edge density of the image. First, JPG is a lossy compression method of digital images, so a visually complex image with many perceptual features takes up more storage space than a simple image (Pieters, Wedel, and Batra 2010). Alternatively, researchers use edge density, or the percentages of edges in a picture, to measure feature complexity (Purchase, Freeman, and Hamer 2012). The edges of an image denote where color or brightness changes dramatically, so they typically represent the boundaries, textures, or contours of objects (Szeliski 2010; Figure 6). A complex image with rich perceptual details would have a high percentage of the area detected as edges (Purchase, Freeman, and Hamer 2012). The present study used the Canny edge detection algorithm in OpenCV and measured the percentage of edge points in the image. These two measures are highly correlated ($r = .88$). After standardization, we combined them into one measure, which can be utilized as a reliable, valid, and objective measure of feature complexity.

Compositional Complexity

This complexity refers to whether the elements in an image are located in a clean background or spread across the whole image (Peng and Jemmott 2018). Two indicators were used. First, an image of the simple composition should have a clean background with edges clustered in a small region so edge points are closer to one another. A complex composition picture should have edges in the entire image, so edge points are far away from one another. Therefore, two indicators include the mean of euclidean distances among all the pairs of edge points and the relative size of the smallest bounding box that contains at least 90% of edge points ($r = .89$, see Figure 6).

Color Variety

To measure the color variety, we took two measures. First, after calculating the percentages of different colors in the image (Figure 5), we used the Shannon index, a measure of diversity in proportions, to reflect the variety in the detected colors. Color variety is calculated as follows:

$$C = -\sum_{i=1}^{8} p_i lnln\ lnln\ p_{\ i},$$

Figure 7. Images that score high or low on selected visual features.

where p_i represents the percentage of one of the eight chromatic colors (i.e., red, orange, yellow, green, blue, pink, purple, and brown).

The second measure was based on the hue count formula proposed by Ke, Tang, and Jing (2006). This formula first converted this image into the HSV color space and kept color pixels that were perceptually colorful ($S > 0.2$, $0.15 < V < 0.85$). Then, we divided the hue continuum into 20 bins and counted the percentages of pixels that fell into each bin. We then counted the bins with enough pixels that passed a threshold. These two indicators of color variety were correlated ($r = .56$) and combined into one measure. Figure 7 shows examples of all visual features.

Step 2.2: Human Evaluations Collection

Next, we collected survey data from human participants to understand how these images shaped the perception of brand personality.

Table 1. Multilevel regression results.

Variable	Sincerity Model 1	Excitement Model 2	Competence Model 3	Sophistication Model 4	Ruggedness Model 5
Brand effects					
Brand (Calvin Klein)	−0.099***	.031**	−0.007	−0.008	.020*
Brand (Converse)	−0.133***	.020	−0.031**	−0.035**	.051***
Brand (Glossier)	−0.042***	.026*	−0.030**	−0.082***	.084***
Brand (Herschel Supply)	−0.057***	−0.048***	−0.029**	−0.016	−0.030**
Brand (H&M)	.037***	.034***	.061***	.057***	.152***
Brand (Urban Outfitters)	.044***	.040***	.070***	.092***	.022*
Participant characteristics					
Male	.003	−0.010	−0.006	.019	.052**
Age	−0.047**	−0.044*	−0.059**	−0.117***	−0.070***
Instagram use	.0128***	.134***	.148***	.138***	.083***
Computer vision features					
Blue	.040***	.005	.008	.019	.095***
Brown	−0.020	−0.018	−0.026*	−0.006	−0.011
Grey	.003	−0.005	.002	−0.001	.004
Green	−0.003	−0.037***	−0.035***	−0.026*	.047***
Orange	.037***	−0.017	.016	.018	.018
Pink	.006	.005	−0.003	.000	−0.030**
Purple	.008	−0.012	.001	−0.004	.021*
Red	−0.011	.008	.020*	.030***	−0.016
Yellow	.018	.000	.014	.006	.018*
Hue	−0.018	−0.011	.013	.005	−0.030**
Brightness	.046***	−0.020	.009	.037***	−0.026**
Colorfulness	.002	.048***	.012	−0.018	−0.012
Feature complexity	.098***	.065***	.058***	.068***	.037***
Compositional complexity	.021	−0.020	.006	.015	−0.000
Color variety	.041***	.042***	.014	.021*	.015
Estimates of covariance					
Residual	.618	.604	.564	.631	.536
Participant ($N = 1{,}507$)	.306	.356	.385	.294	.393

Note. $N_{\text{observation}} = 10{,}549$. Regression coefficients were standardized.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Step 2.2a: Survey Development

The main variable measured in the survey is brand personality. Brand personality was measured on five dimensions for each image (Aaker 1997). All items were measured on a 5-point scale (1 = *Not at all*, 5 = *Very much*). Sincerity was measured by being down to earth, honest, wholesome, and cheerful ($\alpha = .87$). Excitement was measured by being daring, spirited, imaginative, and up to date ($\alpha = .83$). Competence was measured by being reliable, intelligent, and successful ($\alpha = .85$). Sophistication was measured by being upper class and charming ($r = .50$). Finally, ruggedness was measured by being outdoorsy and tough ($r = .59$).

Step 2.2b: Survey Distribution

A total of 1,507 participants located in the United States were recruited from Amazon.com's Mechanical Turk (MTurk) and viewed seven images (one image per brand) through an online survey on Qualtrics. Each image was randomly assigned to each participant. After viewing each image, participants were asked to evaluate perceived brand personality based on the given image. Each image received approximately 14 to 16 ratings on the five dimensions of brand personality.

Step 3: Data Integration

Our study's unit of analysis is one brand personality rating from one participant for one image. Each participant rated seven images, so the sample size was 10,549 (7×1507). We first converted the survey responses from Qualtrics from a wide form to a long form, so each observation represented one rating. We then merged this data set with image features calculated from computer vision algorithms.

Step 4: Data Analysis

Given that each participant viewed seven images in total, we used multilevel modeling with the images nested in participants (allowing for random intercepts; Milkman and Berger 2014). In all regression models (1 through 5), all computer-analyzed visual features were predictors of the brand personality rating, and one brand personality rating per participant was one observation. Participants' age, gender, and usage of Instagram and brand effects (with six dummy-coded brand variables) were also included as covariates. All models controlled for participant and brand characteristics as fixed effects, with participants ($N = 1{,}507$) entered as random effects (see Table 1 for results).

Results

Sincerity

Results indicated that the color blue ($\beta = .040$, $p < .001$), the color orange ($\beta = .037$, $p < .001$), brightness ($\beta = .046$, $p < .001$), feature complexity ($\beta = 0.097$, $p < .001$), and color variety ($\beta = .041$, $p < .001$) were significant predictors of brand sincerity.

Excitement

Results from regression analysis suggested that colorfulness ($\beta = .048$, $p < .001$), feature complexity ($\beta = .065$, $p < .001$), and color variety ($\beta = .042$, $p < .001$) were positively correlated to brand excitement. However, the color green negatively influenced perceptions of brand excitement ($\beta = -0.037$, $p < .001$).

Competence

The regression analysis on brand competence suggested that the color brown ($\beta = -0.026$, $p = .023$), the color green ($\beta = -0.035$, $p < .001$), the color red ($\beta = .020$, $p = .037$), and feature complexity ($\beta = .058$, $p < .001$) were significant predictors.

Sophistication

The regression results suggested that the color red ($\beta = .030$, $p = .004$), brightness ($\beta = .037$, $p < .001$), feature complexity ($\beta = .068$, $p < .001$), and color variety ($\beta = .021$, $p = .041$) were positively correlated to perceived brand sophistication, but the color green ($\beta = -0.026$, $p = .013$) negatively influenced perceptions of brand sophistication.

Ruggedness

Results showed that the color blue ($\beta = .095$, $p < .001$), the color green ($\beta = .047$, $p < .001$), the color purple ($\beta = .021$, $p = .014$), the color yellow ($\beta = .018$, $p = .043$), and feature complexity ($\beta = .037$, $p < .001$) were positively correlated to perceived ruggedness, whereas the color pink ($\beta = -0.030$, $p = .001$), hue ($\beta = -0.030$, $p = .006$), and brightness ($\beta = -0.026$, $p = .006$) displayed a negative relationship with ruggedness.

Discussion

The present research proposes an analytical model for studying visual aesthetics for brand communication on social media. This model provides a holistic view of visual aesthetics denoted by two aspects: color and visual complexity (see Figure 1). The study findings suggest the strong predictive power of visual features for brand personality.

Brand sincerity positively associates with blue and orange. Blue compositions denote peacefulness (Hsieh et al. 2018), relaxation (Bakhshi and Gilbert 2015), and security (Labrecque and Milne 2012), which may evoke pleasant feelings and a sense of calmness (Yu and Egger 2021) and result in greater perceived sincerity. Brightness, linked with the perception of calmness, cleanness, and warmth, also increases the perception of brand sincerity (Gorn et al. 1997).

Brand excitement positively associates with colorfulness and color variety. The saturation and variety of colors stimulate strong emotional responses and evoke arousal (Hagtvedt and Adam Brasel 2017), leading consumers to associate these physiological responses with the brand and perceive greater brand excitement (Labrecque and Milne 2012). In contrast, green, as the analogous color of blue with a shorter wavelength, is perceived as calming (low-intensity emotion) and attenuates brand excitement.

Brand competence and sophistication positively relate to red but negatively associate with green. A red color scheme (e.g., red and pink) denotes a sense of playfulness, activity, and stimulation (Fraser and Banks 2004), which may align with the aesthetic values of lifestyle brands, resulting in greater brand competence. Although green is related to security (Labrecque and Milne 2012), reliability, and support (Fraser and Banks 2004), they may not be considered key values that drive brand competence for lifestyle brands. The findings suggest that the perception of brand competence may be associated with different colors contingent on product categories because consumers may characterize functionality as brand competence for technological products but associate hedonic benefits with lifestyle brands. Moreover, brand sophistication positively links to brightness. High brightness is associated with scarcity, prestige, and luxury (Golden and Zimmerman 1986), characterized by the prescription of charm and glamour (Mahnke 1996), enhancing perceived sophistication.

Brand ruggedness relates positively to the colors blue, green, and yellow and hue but negatively to pink and brightness. Green and blue are linked to ruggedness through associations with nature, such as oceans and forests, which may create feelings of security (Kaya and Helen 2004) and a connection with the outdoors (Clarke and Costall 2008). Similarly, a higher hue value indicates more blue. In contrast, an image composed of more pink colors may reduce consumers' perceived ruggedness of the brand because of the disconnection between the pinkish color and masculinity that characterizes brand ruggedness (Labrecque and Milne 2012). Greater brightness decreases the feeling of control (Valdez and Mehrabian 1994) and thus has a negative relationship with ruggedness (Labrecque and Milne 2012)

While previous research suggests that visual complexity exerted different effects on brand personality (positively related to excitement, competence, and ruggedness but negatively related to sincerity and sophistication), the current study shows that feature complexity (as one dimension of visual complexity) consistently increases perceived brand personality in all five dimensions. Consumers favor images with a diversity of elements, textures, and shapes (Peng and Jemmott 2018) and perceive these complex designs as more visually informative and engaging (King, Lazard, and White 2020; Sharma and Peng 2023). Therefore, feature complexity could serve as a brand personality booster to be used along with other visual features. Our findings on lifestyle brands support the notion that "less is a bore."

Methodological Implications

This study also makes methodological contributions by introducing computer vision methods in analyzing branded images on social media. The proposed method brings several advantages to studying visual content in advertising. First, computer vision methods can be easily applied to large-scale visual images that may otherwise require substantial human labor to analyze. It also provides objective and standardized measures. For example, it may be difficult to instruct human coders to estimate the percentages of a certain color in a brand image. In contrast, computational tools could categorize pixels into color categories. The code to replicate the analysis also allows researchers to facilitate future research. Moreover, we provide a detailed step-by-step procedure to demonstrate how advertising scholars may integrate computer vision analysis with traditional empirical methods like surveys.

Limitations and Future Studies

One limitation of our study is that we exposed participants to various branded images without informing them of the brand account source from which these images were retrieved. As consumers' brand perceptions are often developed from a long-term consumer–brand relationship, other potential factors could contribute to brand personality perception in the real world. Future research may conduct follow-up experiments to examine further the interactions between visual features and other predictors for brand personality (like brand familiarity). Moreover, this study investigates aesthetic attributes only in predicting brand personality; other visual features could also play a role. For example, prior research showed that the facial expressions of models may influence perceived brand image (Yang et al. 2021), and future research can apply computer vision techniques, such as facial recognition and emotion analysis, to broaden the scope of investigation. Finally, while the present study focuses on perceived brand personality, visual aesthetics influence various outcomes, such as emotional responses to advertisements (Lajante et al. 2022) and perceived comprehensibility of visual messages (Lazard and Mackert 2014). Future research can consider how visual aesthetics contribute to other communication outcomes.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

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