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COLOR ANALYTICS FOR DATA-DRIVEN BRAND COMMUNICATIONS

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Color Analytics for Data-Driven Brand Communications

Abstract

Color is an important component in brand visual communication. Firms select brand colors to align with the brand's strategic positioning goals. Despite their importance, brand color decisions are often driven by intuition and trial and error.

We introduce BRACE (BRand Attribute and Color Engine), a predictive model and genetic-algorithm based optimization framework, that generates color palettes that reflect combinations of brand characteristics. Using theory on color combinations and color harmonies, the model avoids contradictions across characteristics while maintaining visual harmony. For example, if a brand seeks to be perceived as Friendly and Glamorous, or highly Outdoorsy but not Young, we recommend aesthetically appealing color palettes that best capture these attribute combinations. We validate the algorithm through a series of experiments. We also find that real ads recolored with recommended palettes are rated significantly higher on the intended brand characteristics. We further use topic modeling to provide interpretable insights into the relationships between characteristics and colors, and how these relationships vary across product categories.

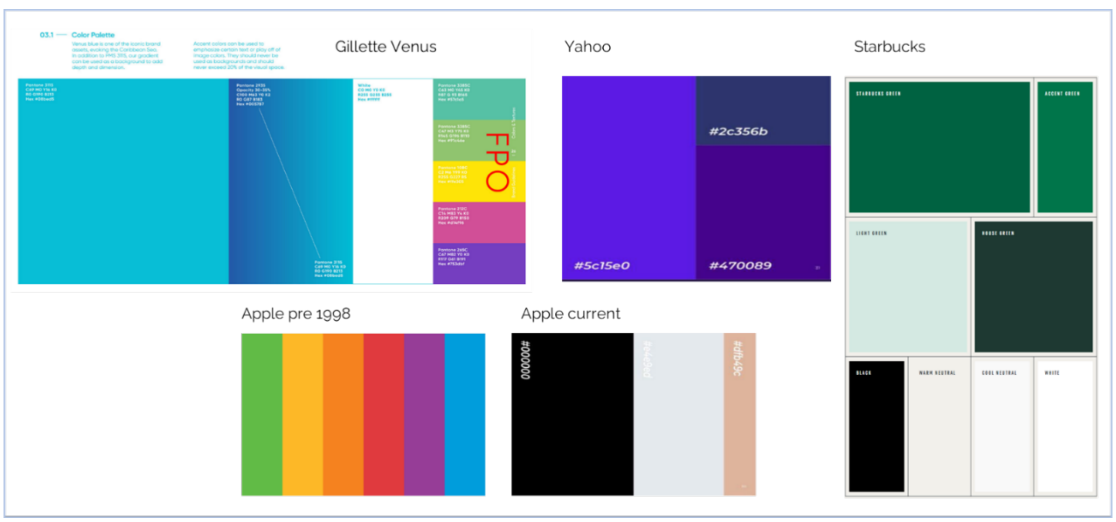
This paper is a major step towards data-driven brand visual communication that can better align creative choices with communication goals.

Keywords

Image analytics, branding, color, machine learning, genetic algorithm, topic modeling, brand personality, BRACE.

Color decisions guide the design of products, packaging, online and offline retail outlets, and digital and traditional advertising (Gorn et al. 1997; Labrecque and Milne 2012; Wedel and Pieters 2015; Dew, Ansari, and Toubia 2022). Apple, for example, uses monochrome colors with black and shades of grey[1]. Instagram, on the other hand, uses a combination of several distinct bright colors[2]. Starbucks has changed its colors several times, and in 1987 introduced the brand's "iconic green" (Phillips and Rippin 2010). Brand managers and designers work together to develop brand books that define, among other things, the exact shades of colors to be used in all the brand communications. Figure 1 presents examples for the colors from the brand books of Gillette-Venus, Yahoo, Starbucks, and Apple.

Figure 1: Brand colors from the brand books of Gillette Venus, Yahoo, Starbucks and Apple



Color decisions can backfire if made incorrectly. For example, Tropicana's 2009 rebranding campaign, which reportedly cost $35 million, led to a $27.3 million sales decline; while the exact cause for the failure is difficult to isolate, the redesign included a substantial shift in the brand's color palette from warm oranges and greens to more electric shades (Lee, Gao, and Brown 2010).

1 http://www.macmothership.com/gallery/gallery1.html

2 https://about.instagram.com/brand

Brand colors are selected to serve the brand's strategic positioning. Often, the positioning is defined through a set of characteristics related to brand personality (Aaker 1997) or brand equity (Mizik and Jacobson 2008). A brand may want to be perceived as Cheerful and Friendly, or Technical and Imaginative, differentiated from or prototypical to its category. Yahoo, for instance, claims that purple, its signature color, serves the brand's positioning as "whimsical" (McCracken 2015) and as an "amplification brand, amplifying the things that matter".[3] Abercrombie & Fitch differentiated itself by not selling black clothing, and even forbade its employees to wear them for work since "we are a casual lifestyle brand and feel black clothing is formal" (Lutz 2013).

Despite the key strategic role of brand colors, and even as firms move towards data-driven marketing and Gen-AI design (Wedel and Kannan 2016; Hartmann, Exner, and Domdey 2025; Heitmann 2024), color decisions often remain a creative task, based on personal artistic interpretation, aesthetic considerations (Dondis 1973; Samara 2005), and sometimes general findings on the associations of colors outside the branding context (e.g., yellow means Cheerful, see Wexner 1954). As a result, there is a large variation between the suggested colors for a particular brand positioning, even when suggested by professional designers (see Web Appendix A for a demonstration of discrepancy in designers' recommendations).

While large, established brands, such as Gillette, Starbucks and Apple, have rich experience in their respective categories and can afford high quality design teams and intensive testing procedures, many other brands are not that privileged. They hire an agency, provide it with a brief, receive a suggested design, and, at best, run a limited number of test rounds without having a clear reference as to whether their chosen colors support their branding goals. Even when using

[3] https://www.pentagram.com/work/yahoo/story#:~:text=The%20strategy%20positions%20Yahoo%20as,that%20literally%20stands%20for%20amplification

generative AI engines to create a large set of visuals in different colors, testing them requires considerable resources. A systematic, data-driven, interpretable and quantitative framework that relates brand characteristics to colors will reduce the uncertainty and, ultimately, improve brand visual communications. This paper is a first step in this direction.

Finding a palette of colors that best serves a desired brand positioning is challenging. Brands use *palettes*, or combinations of colors rather than a single color. A combination of colors can have a meaning of its own beyond the meaning of each individual color. For example, the combination of pink and light blue of the Gillette-Venus brand carries different meaning than the combination of light blue and orange of the Gillette-Fusion brand. Therefore, brand-color relationships should be studied based on color palettes and not individual colors. Furthermore, brands typically define their positioning along multiple characteristics (e.g., Feminine, Technical, and Cool) and the chosen brand colors must capture the combination of all characteristics simultaneously. To constitute the palettes, brands have to specify the exact *shades* of the colors they use. Shades which are close to each other in standard color representation schemes such as RGB or HSV, can have vastly different meanings in a branding context. For example, neon green might have a different identity than forest green.

Past research that linked colors to brand characteristics has focused on brand logos. Labrecque and Milne (2012) map brand personality attributes to colors in the context of logos and focus on a set of 11 selected colors. Dew, Ansari, and Toubia (2022) develop a decision support system for designing logos, and demonstrate the relationships between three logo colors and brand characteristics. Logo is a single component of the brand visuals, and is typically limited in the number of colors it uses. The logo of Gillette Venus, for example, has only a single color – light blue. However, the brand visual communication includes a much broader spectrum of colors, used for packaging, advertising, website design, and printed materials.

The goal of this paper is to quantitatively establish the relationships between brand characteristics and colors. We introduce an optimization framework, based on predictive model and genetic algorithms, which we term BRACE (BRand Attribute and Color Engine) to suggest color palettes which capture combinations of brand characteristics, and at the same time are visually appealing. These palettes can be adjusted to specific categories. We validate the algorithm and compare its performance across three datasets. We show that although color is only one component of the brand's visual communication, it is still powerful: recoloring ads in the suggested palettes shifts perception towards the desired characteristics. We further use topic modeling to provide interpretable insights into the relationships between characteristics and colors. We extend the traditional color classification (e.g., yellow, green, brown etc.), and study the entire color space. We explore the source of the color associations and show that characteristic-color associations often go beyond the colors of individual objects linked to the brand.

Our contribution is managerial, substantive, and methodological. Managerially, we provide marketers with a tool to select a color palette for their brand given their positioning goals. The palettes go beyond single-color matching and consist of colors taken from the entire color space. Substantively, we provide a mapping of colors to personality and equity characteristics. We show that color associations exist above and beyond specific objects or scenes related to the brand. We demonstrate how changing the color combination of an ad changes the perception of the brand in the ad. Methodologically, we built a flexible algorithmic framework for brand palette generation which can be trained on a variety of datasets and tuned to the specific brand needs.

This work adds rigor and structure to color branding decisions. It enhances researchers' and practitioners' understanding of the role of color in consumer brand perception to improve how brands, firms and designers work with color. Our approach and findings can streamline the interactions between brand managers and creative teams and ultimately lead to design decisions that align better with the brand's communication goals.

Literature - Color Research in Marketing

Table 1 summarizes relevant papers on color in marketing. The two most related papers are Dew, Ansari and Toubia (2022), and Labrecque and Milne (2012), both of which focus on brand logos. Dew, Ansari, and Toubia (2022) analyze 14 colors of 700 logos of real brands. As part of the exploratory analysis, they demonstrate the relationship between three prevailing colors in logos (black, blue, and red), and brand characteristics. They find, for example, that red is dominant in logos of Down to Earth and Cheerful brands, and less dominant in Upper Class brands.

Labrecque and Milne (2012) conducted a series of lab experiments to test hypotheses on how the five personality dimensions of Aaker (1997) (Sincerely, Competence, Excitement, Sophistication, Ruggedness) relate to the color of the logo and the color of the packaging. They find, for example, that an orange logo is negatively associated with Sincerity and Sophistication, while purple, pink and black logos are positively associated with Sophistication.

Taking a deep learning approach, Liu, Dzyabura and Mizik (2020) trained predictive neural network model to identify the four brand characteristics (Rugged, Glamorous, Healthy, and Fun) from social media images., but did not attempt to connect brand characteristics with specific colors.

Table 1: Literature on colors in marketing

Paper	Research focus	Colors studied	Dependent variable	Image source	Links color to brand characteristics	Color combinations?	Multiple shades of a color?
Dew, Ansari & Toubia (2022)	Logo	14 colors extracted by K-means clustering from brand logos	Brand personality (Aaker 1997)	~700 brand logos	V		
Labrecque & Milne (2012)		1: 11 colors treated individually 2: Low/high saturation X low/high value X (red, green, blue and purple)	Brand personality (Aaker 1997) + brand familiarity and likability	Lab generated logos	V		V
Jalali & Papatla (2016)	Social media	6 hues: red, yellow, green, cyan, blue, and violet, the average saturation and value for each hue in the photo	Number of clicks on the picture	Brand Instagram photos			V
Wedel & Pieters (2015)	Advertising	Color vs Grayscale in different levels of blurriness background color in short exposure	Recognition of: Ad vs. Not, product category, brand name	Lab generated ads			
Gorn et al. (1997)		32 combinations treated individually - red & blue X 4 saturation levels X 4 value levels	Excitement, Relaxation, Unpleasantness + ad liking	Lab generated ads			V
Zhong et al. (2020)	Product design	Warm vs. cold hues, saturation, brightness, contrast, image clarity	Demand for an AirBnB property	AirBnB properties		V	
Dzyabura et al. (2023)		30 colors extracted by K-means clustering from product images	Return rate of clothing items	Clothing images			
Deng et al. (2010)		16 colors used by NIKEiD shoe configurator	Likelihoods of color pairs	NIKEiD shoe configurator		V (pairs)	
Hagtvedt & Brasel (2017)		Red, green, blue in different saturation levels	Product perceived size	Lab generated packages			
Lunardo, Saintives & Chaney (2021)	Packaging	Red, green, blue	Guilt about food consumption	Lab generated packages			
Mead & Richerson (2018)		Different levels of saturation	Food healthfulness perception	Lab generated snack packages			
This Research	Brand Perception	111 color clusters	47 brand characteristics: Brand personality and BAV brand equity	Directly elicited brand collages; Flickr; Instagram	V	V	V

As Table 1 indicates, besides Dew, Ansari, and Toubia (2022) and Labrecque and Milne (2012), the marketing color literature does not directly address brand characteristics. The bulk of this literature has focused on the use of color in individual elements of the marketing mix. Wedel and Pieters (2015) and Gorn et al. (1997) explore how the colors in an ad impact consumer cognitive and emotional response to the ad. Jalali and Papatla (2016) study how colors of social media images influence click rates. In product design, Deng et al. (2010) allow respondents to design shoes and calculate the likelihood of pairs of 16 possible colors to appear in the designs. Hagtvedt and Brasel (2017) demonstrate that the color of a product affects its perceived size. Dzyabura et al. (2023) measure how 30 different clothing colors are related to online product return rates. In food packaging, color impacts the perception of the food's healthfulness (Mead and Richerson 2018) and feelings of guilt about food consumption (Lunardo, Saintives, and Chaney 2021).

We extend the existing literature in three important directions. First, these papers mostly focus on single colors. However, brand managers use palettes or combinations of colors rather than a single one. A combination of even two colors may create a perception different from each individual color, therefore, it is important to identify meaningful combinations of colors and relate them to brand characteristics. Second, with the exception of Dew, Ansari and Toubia (2022), and Labrecque and Milne (2012), the color associations in these studies do not relate to brand metrics such as brand personality and brand equity, which are the foundations for firm's brand positioning goals. Even these two remain silent as to what should a brand do if it needs to combine several characteristics that are represented by different colors. Third, colors come in many shades, but most existing literature reduces the analysis to a small number of colors. Fourth, these papers focus on logos, ads and packaging, which are specific brand elements generated by firms, and do not measure the colors consumer actually associate with the brand.

This paper bridges the gap between existing knowledge and the needs of brand managers and design teams. The framework we develop focuses on color combinations, and attaches a color palette for weighted combinations of characteristics (e.g., high on Exciting, low on Young). We account for a comprehensive set of brand characteristic and a broad set color shades. We train and validate all the models and results on the way consumer perception of the characteristic-color relationships. The resulting tool, BRACE, provides a solution to the managerial color choice decision. BRACE palettes are theoretically grounded, data-driven, and empirically validated, and can shift consumer perception of brand visual communication towards the desired positioning.

Theoretical Foundation

Colors have been studied across a wide range of disciplines, including art and design, psychology, physics, computer science, and biology. Each field offers a distinct perspective. In this section we integrate several of these perspectives. We discuss the semantic meanings of colors from the psychology literature, and connect them with branding theory to understand the role of colors in brand perception. We place particular emphasis on color combinations, a central topic in art and design that has received scant attention in marketing research.

Color Theory and Color Representation

Color theory explains how colors are structured and combined to create coherent visual impressions (Munsell 1905; Itten 1970). It examines the ways in which individual colors and color combinations influence perception, meaning, and aesthetic response.

A central element of color theory concerns color representation. While most languages include names for only a limited set of colors (Kay and Regier 2003), the number of physically and digitally distinguishable color shades is extremely large. Early color-order systems arranged colors in a circle, known as the color wheel, based on three primary colors and their mixtures.

The Munsell system (Munsell 1905; Kuehni 2015) advanced this approach by describing colors in a three-dimensional space that approximates perceptual uniformity: hue (e.g., red or blue), value (lightness from white to black), and chroma (saturation or vividness).

In digital environments, color is typically represented in models such as RGB, where each color is encoded as an additive mixture of 256 levels of red, green, and blue light intensities. This structure produces 256^3, or roughly 17 million, possible color shades. The same RGB triplet may appear differently across screens depending on the characteristics of the specific device (Wyszecki and Stiles 2000). To address this, color science developed device-independent and perceptually oriented color spaces such as CIE XYZ and CIELAB (CIE 1976), in which Euclidean distances more closely approximate perceived color differences.

Building on these representations, image processing research treats colors as structured data. Clustering algorithms, for example, extract dominant colors from images, allowing researchers to summarize palettes, compare visual styles, and capture structural properties of colors across large collections of images (Plataniotis and Venetsanopoulos 2000). These computational methods operate independently of semantic meaning, yet they reveal meaningful patterns, indicating that color carries structured information even before interpretation.

The Associations of Colors

Color has been shown to influence moods and emotions (Wexner 1954; Valdez and Mehrabian 1994), performance on cognitive tasks (Mehta and Zhu 2009), preferences (Semin and Palma 2014), behaviors such as aggressiveness among jail inmates (Schauss 1981), and perception in other sensory modalities such as taste (Wang and Chang 2022).

Colors carry meaning and are consistently linked to specific associations. Interestingly, this meaning goes beyond specific objects (Schloss 2018). Red has been linked to Excitement

(Wexner 1954; Gorn et al. 1997) and Anger (Wexner 1954; Kaya and Epps 2004); Blue to Relaxation (Gorn et al. 1997; 2004), Security (Wexner 1954), Calmness (Wexner 1954; Kaya and Epps 2004), and Logic (Mahnke 1996); White to Cleanliness and Purity (Clarke and Costall 2008; Tham et al. 2020), Femininity (Semin and Palma 2014), and Simplicity (Mahnke 1996; Fraser and Banks 2004). Brown is related to Earthiness (Clarke and Costall 2008) and Boredom (Tham et al. 2020); Black to Power (Wexner 1954) and Masculinity (Semin and Palma 2014); Green to Peacefulness (Clarke and Costall 2008), Calmness (Kaya and Epps 2004), Health and Nature (Tham et al. 2020); Pink to Femininity (Clarke and Costall 2008; Tham et al. 2020) and Romance (Cerrato 2012). Yellow evokes Cheerfulness (Wexner 1954; Clarke and Costall 2008; Cerrato 2012) and Happiness (Kaya and Epps 2004). Figure 2 summarizes these findings.

Figure 2: Summary of color associations

Red	Blue	White	Brown	Black	Green	Pink	Yellow
Excitement	Relaxation	Cleanliness	Earthiness	Power	Peacefulness	Femininity	Cheerfulness
Anger	Security	Pureness	Boredom	Masculinity	Calmness	Romance	Happiness
	Calmness	Femininity			Health		
	Logic	Simplicity			Nature		

Where do such color associations come from? We integrated the literature into four potential sources, summarized in Figure 3: ***physiological factors***, ***cultural patterns***, ***personal factors***, and, specifically related to the context of this paper, ***collective branding activities***.

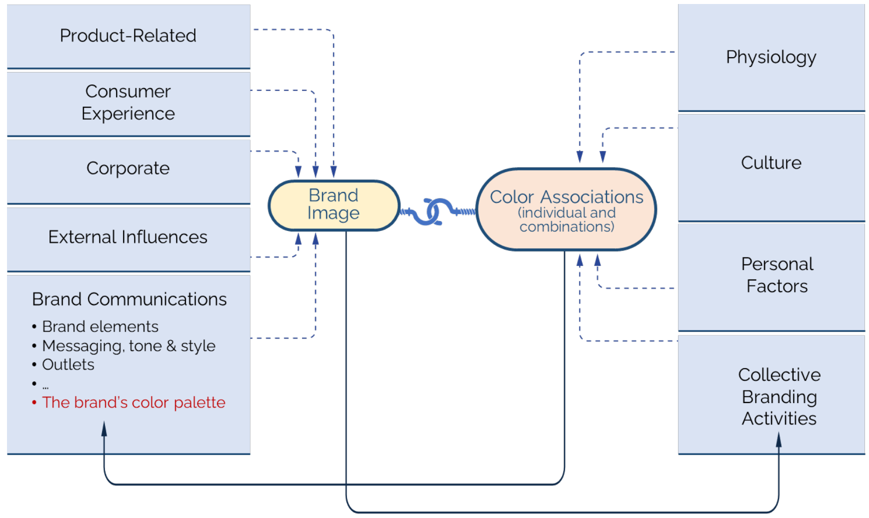
Some color associations are rooted in ***physiology*** and may have evolved over the course of human development. For example, Meert, Pandelaere, and Patrick (2014) show that both adults and children prefer glossy over matte surfaces. They argue that this preference reflects an adaptive response to the visual properties of water, as water was historically an important resource. Semin and Palma (2014) suggest that females prefer lighter colors and males darker ones, due to gender differences in skin tones.

Color perception can vary by ***culture***. Madden, Hewett, and Roth (2000) found that blue, green, and white were consistently associated with Peaceful, Gentle, and Calming qualities across eight countries, but respondents in Brazil, Hong Kong, China, and the United States also linked these colors with Beauty. Jacobs et al. (1991) report that purple was perceived as Expensive in Japan, China, and South Korea, but as Inexpensive by respondents in the United States.

Personal factors further shape color associations. Extroverts prefer vivid greens and pinks and conscientious individuals lean toward orderly blues and reds (Matz et al. 2019; Jue and Ha 2022). Elliot and Maier's Color in Context Theory (2012) and Schloss's Color Inference Framework (2018) suggest that repeated pairings of color with concepts and experiences shape color associations. Someone may associate khaki with gentleness due to memories with their grandparents, while another may link it to military environments.

In this paper we focus on brands, and therefore highlight another important factor: ***collective branding activities***. Brands leverage cultural and innate associations. At the same time, they also *shape* associations with a color through consistent visual communication (consistent with Elliot and Maier (2012) and Schloss (2018)). Tiffany, for example, created its signature Tiffany Blue (Pantone 1837), by choosing a relatively neutral color in terms of association, which was not even included in the standard Pantone guide, and linking it with luxury and style through persistent brand messaging. Similarly, Mattel's long history of promoting Barbie Pink (Pantone 219C) has tied the color to playful luxury, optimism and joy, and accessible glamour. The immense marketing efforts over decades have extended the associations of these colors beyond the brand alone and have made them a part of the broader pool of color associations.

Figure 3: Conceptual framework: How brand color palette serves desired brand image and overall color associations



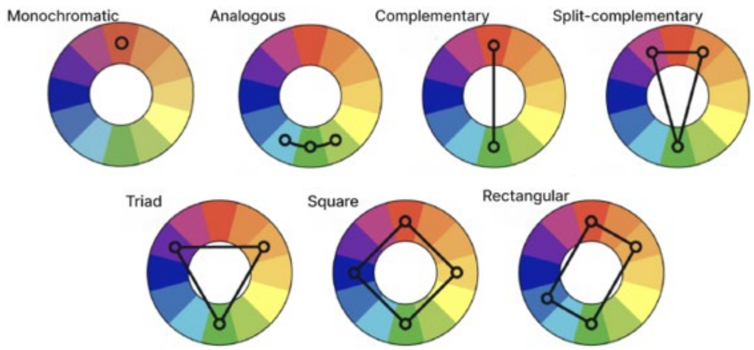
Color Combinations and Harmonies

Color theory emphasizes combinations. Out of the virtually infinite number of combinations, designers seek harmonious ones: aesthetically pleasing and creating a sense of balance, unity, or visual order (Westland, Laycock, and Cheung, 2007; Weingerl and Javoršek 2018). Standard design guides, such as the Pantone Color Harmony series, propose combinations based on the relative positions of colors on the color wheel (Jacobson and Ostwald 1948; Eiseman 2017).

Itten (1970), whose harmonies we use for this research, formalized harmonic "chords" derived from geometric relations among hues on the color wheel. As illustrated in Figure 4, he defines seven harmony types: monochromatic (variations of a single hue), analogous (adjacent hues), complementary (opposite hues), split-complementary, triadic, tetradic, and square. Schloss and Palmer (2011) show that perceived harmony for color pairs increases with hue similarity, although high-contrast combinations may be preferred when serving distinct figure–background roles. Similarly, Deng, Hui, and Hutchinson (2010) find that consumers prefer pairing similar shades in shoe design. Computer science extended the research to multi-color palettes (Szabó, Bodrogi, and Schanda 2010; Weingerl and Javoršek 2018). Based on their principles, Westland, Laycock, and

Cheung (2007) propose models for measuring harmony using hue similarity, chroma balance, and lightness variation, and Cohen-Or et al. (2006) apply such models to harmonize complex images.

Figure 4: Colors harmonic chords (adapted from Itten (1970))



Consumer responses to a color pair depends on the affective qualities of its components (Allen and Guilford 1936). In addition, combinations can generate associations beyond those of the individual hues. Madden, Hewett, and Roth (2000), find that black with red signals happiness in Chinese culture and is commonly used in wedding invitations; red paired with white represents celebration and vitality in Japan. In design, the Pantone color scheme (Eiseman 2017) maps 648 three-color combinations into 24 descriptive emotions: Serene, Earthy, Mellow, Muted, Capricious, Spiritual, Romantic, Sensual, Powerful, Elegant, Robust, Delicate, Playful, Energetic, Traditional, Classic, Festive, Fanciful, Cool, Warm, Luscious & Sweet, Spicy & Tangy and Unique.

The theoretical treatment of color combinations addressed combinations of two or three colors. However, real brand color palettes can include more colors. Consequently, there is a need to incorporate these higher-order interactions, and our research advances this direction.

The Color Associations of Brands

Brands are often conceptualized as associations: symbols, experiences, and marketing mix elements that come to mind when consumers think about a brand. These form the brand image: the collective perception of the brand held in memory (Keller 1993; John et al. 2006).

The brand image creates a schema in consumers' minds. A schema represents the perceptions and expectations of a certain domain (Bettman 1979; Halkias 2015). Schema theory explains that individuals strive for conceptual coherence (Murphy and Medin 1985), so they organize concepts into structures (schemata) in memory (Park, Milberg, and Lawson 1991). Individuals hold many schemata, and concepts are encoded and classified to allow easier processing (Sujan and Bettman 1989). A product may belong to a schema due to category (e.g., expectations from beauty brands), a characteristic (a Cool and Exciting brand), or a shared visual feature (brands using blue and red).

Brand image develops dynamically, shaped by multiple factors, as presented in Fig. 3. ***The product*** itself is central; its functionality, quality (Heath, DelVecchio and McCarthy 2011), quality consistency (Gürhan-Canli 2003), and design (Page and Herr 2002). ***Consumers' experiences*** also contribute to brand image formation. As conceptualized by Brakus et al. (2009), they include: product experiences (search, examination, exposure to advertising), shopping and service experiences, and consumption experiences. Such experiences combine with consumers' personal histories and can create emotional bonds and attachment (Thomson, MacInnis, and Park 2005). ***Corporate-level factors*** matter: the strength and meaning of the corporate brand (Brown and Dacin 1997) and social responsibility practices (Torelli, Basu Monga, and Kaikati 2012) can spill over to shape brand perceptions. ***External forces*** beyond the firm's immediate control, including online and offline buzz (Lovett, Peres, and Shachar 2013), product reviews (Chakraborty and Bhat 2018), media coverage, and competitive actions (Gunasti and Devezer 2016), also affect brand image.

In this paper we focus on a major factor shaping brand perception, which is ***the brand's marketing communication***. Brand communications include all brand elements, such as name, logo, slogan, shapes, imagery, and color palette, and appear in message content, tone and style, packaging, store design, and communication outlets. Ongoing marketing communications, along with the other factors, anchor a schema of the brand in consumers' minds and establish its set of associations.

A large part of brand communication relies on visuals (Wedel and Pieters 2008). Humans process visuals efficiently (Kress and Van Leeuwen 1996; Palmer 1999), and associate them with feelings and emotions (Cho, Schwarz, and Song 2008). Visual elements of packaging (Greenleaf and Raghubir 2008), store design (Meyers-Levy and Zhu 2008), advertisements (Pieters, Rosbergen, and Wedel 1999; Wedel and Pieters 2000), and the visual context on which the brand is displayed (Cho, Schwarz, and Song 2008) were found to have significant impact on consumer response.

Within the visual elements, color plays a particularly important role. As shown earlier, colors carry systematic meanings in human perception. In schema theory terms, each color is represented as a schema of associations. In the branding process, the firm defines the desired brand image and then strategically selects the color palette to support this image. These palettes are formalized in the brand book. From this point on, every touchpoint, namely packaging, store design, advertising, digital interfaces, and direct communications, deploys the palette, strengthening the links between the colors and the brand and embedding the palette into the brand's schema.

With consistent investment, consumers begin identifying the color palette with the brand. As demonstrated in Web Appendix B, consumers recognize top brands from their colors alone, even in the absence of any other cues. Therefore, color palettes are not merely aesthetic choices but strategic assets in shaping brand image. It is this strategic role that motivates our research, which helps brands select palettes that convey their desired characteristics.

Overall Theoretical Perspective

Linking the brand to a color palette connects the brand schema with the color schema. When a color appears in brand communications, the associations tied to that color are activated and integrated with the brand image. Conversely, the schema of the color is also enriched due to its association with brands with the specific qualities. For example, the red used by Pizza Hut evokes the Excitement associated with red, yet it may also enrich the meaning of red with associations such as fast food, tomatoes, and spiciness. These relationships are described in Fig. 3.

This framework suggests that brand, colors, and brand characteristics reinforce one another. When consumers interact with brands, multiple schemata are activated, integrating the color's meaning, the brand image, and the category context. Building on this framework, we outline four broad claims to guide our empirical work. First, consumers associate brands with specific colors. Second, color associations extend beyond specific objects tied to the brand and reflect broader conceptual meanings. Third, these associations may vary across categories. Finally, changes in the colors used in brand communication can lead to shifts in the brand perceptions. We do not formalize these as testable hypotheses but rather as general claims that we evaluate across the studies in this paper.

BRACE – Generating Palettes for Combinations of Brand Characteristics

Assigning a color combination to match a desired set of brand characteristics is challenging. Brand managers must select a palette of several colors, out of the nearly infinite number of possible color combinations, that conveys the desired brand image, is aesthetically pleasing, and fits the category context. Moreover, the desired brand image itself is complex: brands rarely seek to maximize a single characteristic, but rather a calibrated position across several characteristics (such as "moderately Exciting" and "not too Young"). The multidimensional nature of this problem calls for a machine-learning–based solution. Our solution, BRACE, integrates principles of color harmony with the associative meaning of individual colors to generate palettes that shift consumers' perceptions toward the desired brand image.

BRACE consists of two modules. The first module is a set of predictive models that take a palette of colors as input and infer the palette's association with each brand characteristic separately. We train these models on a large set of images labeled with brand-characteristic ratings. The second module optimizes the palette that most closely matches the brand's target profile, while ensuring that the resulting palette is harmonious. This module uses the first module as the evaluation function within a genetic algorithm. The genetic algorithm searches the space of possible palettes and identifies the palette that best fits the desired combination of characteristics.

Model Architecture

Module 1: Predictive model

In this module, we train a machine learning model on a large set of image data labeled with brand-characteristic ratings. The objective is to construct a model that, given a color palette, infers the degree to which that palette is associated with each of the brand characteristics of interest. For example, the model evaluates the extent to which a palette is Glamorous.

Pre-processing. We represent the color space using the RGB system. We apply K-Means clustering to compress the RGB space into a set of 128 representative clusters. Each pixel in an image in the training set is assigned to its nearest centroid using Euclidean distance in RGB space.

Next, we eliminate pixels corresponding to background, which is mostly pure white (RGB 255, 255, 255). We reduce redundancies among visually similar neutral tones, such as blacks and greys: we convert the centroids into HSV (Hue, Saturation, Value) and compute a score $Z = S * V$, for each. Centroids scored below threshold $\bar{Z} - stdev(Z)$, are either merged or removed. Thus, we merge six black clusters into one, four light grey clusters into one, and four dark grey clusters into one. We eliminate six additional low-chroma centroids. The resulting space consists of 111 core colors. For each image m in the training set, we construct a feature vector v_m that represents the relative proportions of the 111 core colors $v_m = (s_{m1}, s_{m2}, \ldots, s_{m111})$, where s_{mn} denotes the proportion of the n-th color in image m, such that $\sum_{n=1}^{111} s_n = 1$.

Model training. Each brand characteristic is represented as its own non-linear function $f(v_m)$ of the color composition in image m. We estimate a separate model for each characteristic, using XGBoost (Extreme Gradient Boosting), which performs well in settings with many features and highly nonlinear relationships between features and response. We compared XGBoost to several alternatives, including OLS, Lasso, and a fully connected neural network, and found XGBoost to deliver superior performance. All variables are standardized to ensure numerical stability.

Module 2: Optimization - finding the palette that best represents the desired characteristics

Let y_{target} denote the brand's desired positioning in the brand-characteristic space. This vector $y_{target} \in R^K$ specifies target scores on a 1–5 scale (where 5 is the highest), for *K* distinct characteristics. For example, a brand that aims to be 5 on Down to Earth, 2 on Spirited, and 4 on Imaginative defines a target vector y_{target} (5,1,4), with *K*=3.

For any candidate palette v , we define its fit as the inverse squared distance between the palette inferred score $f(v)$, as predicted by the XGBoost models, and the target y_{target}:

(1) $$\left(f(v) - y_{target}\right)^{-2}.$$

Only the characteristics specified in the brand's target profile are included in the fit calculation. Characteristics that are not explicitly part of y_{target} do not influence the optimization and therefore have no impact on the palette's fit score.

Harmony Constraint. To create visually appealing palettes, we incorporate a harmony constraint $h(v)$. This constraint is built on the seven harmonies from in Itten's (1970) color theory (see Fig. 4). For a given palette *v*, let *n* denote the number of harmony types present in the palette (e.g., analogous, complementary, triadic). We define the harmony score as:

$$h(v) = \begin{cases} \sqrt{n}, if\ n > 0 \\ -1, otherwise \end{cases}. \quad (2)$$

This formulation rewards palettes with harmonic structure and penalizes those that lack it.

The objective function. We combine the harmony constraint with the fit function in Eq. (1) to obtain the optimization objective:

$$v^* = \arg\max_v \left(f(v) - y_{target}\right)^{-2} * h(v)). \quad (3)$$

Given this specification, palettes that lack harmony receive a negative score and are never selected. As a result, only harmonious palettes are eligible.

Palette generation: genetic algorithm. The objective function in Eq. (3) is non-differentiable and non-convex, because $f(v)$ is modeled with non-linear tree ensembles. It cannot be optimized by computing derivatives and setting them to zero, since it has no usable gradients and contains multiple local optima. Therefore, we use a genetic algorithm, which efficiently searches the palette space for v^* without requiring smoothness or convexity in the objective function.

Genetic algorithms are inspired by natural selection. They begin with a *population* of candidate solutions, or *individuals*, and iteratively improve them by selecting high-performing candidates and combining them to produce the next generation (Sivanandam and Deepa 2008).

In our setting, an individual is a candidate color palette v_j, whose elements, or *genes* are the proportions of each color. The population size is 100 palettes across all iterations. The initial population is formed by sampling color proportions from a uniform distribution.

At each iteration, the fit of all palettes in the population is computed according to Eq. (3). 10% are selected as parents based on probabilities proportional to their fitness scores. New offspring are generated using Single Point Crossover, in which two parent palettes are cut at a random index and recombined. This procedure enables the algorithm to integrate effective sub-combinations of colors across different regions of the solution space. To prevent premature convergence to suboptimal palettes, we apply Random Mutation to 10% of the genes in the offspring, introducing small perturbations to the color proportions and allowing local exploration around promising candidates. We use Steady State Selection, retaining the top 10% of palettes and replacing the remaining 90% with new offspring, keeping the population size fixed at 100.

Because individuals with higher scores are more likely to be selected as parents, the average fitness of the population increases over iterations. The algorithm converges, once there is no meaningful improvement across generations. In our setting, convergence is typically reached after 1,000 iterations. The genetic algorithm was implemented using the PyGAD framework.

BRACE provides a general framework for creating color palettes that both express brand characteristics and yield aesthetically harmonious combinations. It can be trained for any set of desired characteristics, provided that an adequate training set of images is available. Naturally, the quality of the resulting palettes depends on the accuracy of the predictive models of module 1, which infers characteristics from color. This accuracy depends on the richness of the training data and the information it contains.

Training Data

Training module 1 of BRACE requires a large set of images labeled with the characteristics of interest (a minimum of 1000 images per characteristic). We focus on 47 brand characteristics drawn from brand personality (Aaker 1997) and brand equity (Lovett, Peres, and Shachar 2014).

As with any machine learning application, the quality and relevance of the training data critically affect the quality of the outcomes. We trained BRACE on three datasets: Flickr images, Instagram brand images, and a dataset of digital collages.

For the first dataset, we used images from Flickr, an online image-sharing platform that has been widely used in prior visual research (e.g., Zhang et al. 2012; Liu, Dzyabura, and Mizik 2020). Flickr users tag the content they upload or view. We collected images tagged with one of the 47 characteristics, altogether ~50,000 images. Note, that while Flickr photos are colorful and of a high quality, and the labeling is rich. it has relatively few photos describing brands, and therefore lacks explicit branding context. This makes it a great database to describe qualities, but it is not ideal for brand-related color decisions. For instance, searching for "Young" retrieves many photos of children, which visually differs from what consumers mean when describing a Young brand.

For the second dataset, in order to introduce branding context, we scraped Instagram posts. We collected ~50,000 images containing (in a hashtag or the post text) one of the 47 characteristics plus a brand name (taken from a large brand list containing over 700 US brands), or a brand-related term such as "brands" or "products". As with any social media, Instagram has limitations for our purpose. It does not contain direct measures of how contributors perceive the brand, and therefore the ratings of the characteristics (e.g., Young 5, Reliable 4) are inferred rather than directly taken from the data. Moreover, despite its popularity, user-generated Instagram content is not equally common for all brands, and some brands (e.g., cleaning products) are significantly less represented than others. Importantly, social media often reflects a biased and potentially strategic set of users (e.g., sellers and influencers). Technically, searching for multiple tags at a time is not feasible, and many posts tagging characteristics are not brand related. As a result, to collect the 50,000 images needed for training, that include both one of the 47 characteristics and a brand related word, we had to download a total of ~1.4 million images, a process which is costly and time consuming.

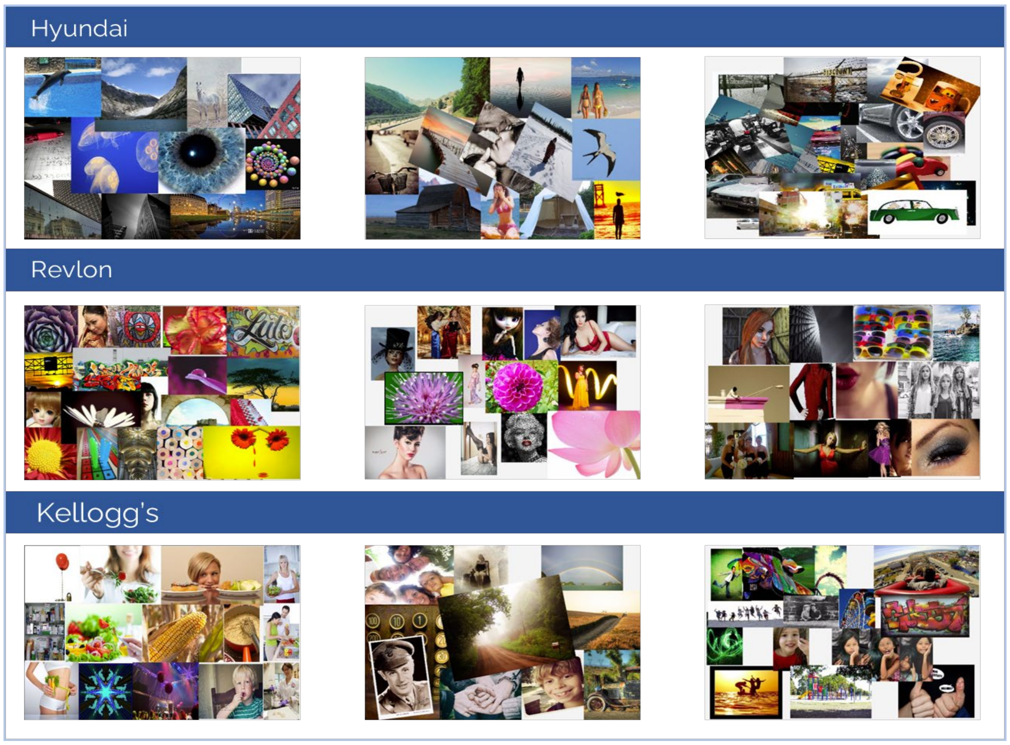
An ideal dataset for our purposes should therefore combine three properties: (1) visual material that reflects consumers' perceptions of brands, (2) coverage of a broad set of brands and categories, and (3) ratings on a rich set of brand characteristics, provided by the same individuals who created the visual material. We obtain such data for our third dataset, from a large-scale direct elicitation study described in Dzyabura and Peres (2021), in which respondents create collages to represent their associations with brands. Collage creation is an expressive technique used in psychology and marketing (Zaltman and Coulter 1995; Koll, von Wallpach, and Kreuzer 2010) that uncovers associations and emotions. Traditionally qualitative, it can be scaled and analyzed quantitatively when implemented digitally.

As explained in Dzyabura and Peres (2021), collages were collected on a specialized platform[4]. Participants first rated their familiarity with a list of brands on a 1–5 scale. Each respondent was then assigned a brand they rated as familiar (4 or 5) and asked to reflect on their emotions, associations, expectations, and prior experiences with that brand. They were then taken to a collage-creation interface consisting of a blank canvas and a large searchable repository of ~100,000 labeled Flickr photos. To provide a broad image repository and ensure that participants could easily locate visuals matching their ideas, the repository was constructed by querying the Flickr API with the 4,000 most frequent English nouns, verbs, and adjectives, and retrieving the first 50 images returned for each query term. Respondents could search or browse this repository, drag photos onto the canvas, and arrange them by moving, resizing, or rotating. In this way, each

[4] http://bvep.researchsoftwarehosting.org/

participant constructed a visual representation of the brand. To encourage respondents to retrieve deep and meaningful associations, the system does not allow respondents to search for the brand itself, other brands in the category, or the type of product. After completing the collage, respondents rated the brand on the 47 characteristics on a 5-point scale.

Figure 5: Examples of collages for Hyundai, Revlon and Kellogg's



We use the dataset collected by Dzyabura and Peres (2021), which includes 3,937 collages created by 1,851 US respondents for 303 brands from nine categories: beauty (40 brands), beverages (65 brands), cars (29 brands), clothing (23 brands), department stores (17 brands), food and dining (84 brands), health (10 brands), home design (16 brands), and household cleaning products (19 brands), 15–30 collages per brand. Respondents were recruited on MTurk (Masters with a minimum grade of 90), and received $2.50 for completing the task. Note, that respondents were not asked specifically about colors, they were asked to be creative and generate any visual representation they thought as adequate. Importantly, the colors in the collages reflect consumers' broader visual associations with the brands rather than simply reproducing logo or packaging colors, making this dataset particularly suitable for training BRACE.

Figure 5 presents example collages for Hyundai, Revlon, and Kellogg's. The collages are rich in color and show substantial variation. Hyundai collages tend to feature light blues and grays, Revlon collages prominently display reds, pinks, and purples, and Kellogg's collages are dominated by greens and yellows. Although some of these colors overlap across brands, they appear in different combinations and proportions, producing distinct visual impressions. Importantly, the colors in the collages do not necessarily mirror the brand's logo, product packaging, or typical marketing materials. For example, Kellogg's logo is red, yet red is not a dominant color in its collages. This pattern illustrates that the collage colors reflect consumers' broader perceptions of the brand rather than the colors in its marketing mix.

We trained BRACE separately on each dataset. Since the Flickr and Instagram datasets do not include brand ratings, we used a variation for the training of module 1, where the XGBoost model is trained in a one-vs-rest setup: for each characteristic, we fit a separate binary gradient-boosted decision tree model that predicts $P(char = 1|v_m)$, where $char$ is the focal characteristic. This gives one calibrated probability per characteristic, which can be then used in module 2. The collage dataset models are trained on an 80% training split, we use 10-fold cross-validation. Flickr and Instagram on are train on 70% (15% validation, 15% test). Hyperparameters are selected via a grid search, yielding a configuration of 160 estimators, maximum tree depth of 9 for the collages dataset (5 for Flickr and Instagram), and learning rate $\eta = 0.02$ for the collage data and 0.07 for the other two.

The out-of-sample predictive accuracy for the models in module 1 for the three datasets is presented in Web Appendix C. Since color is only one component of what makes a picture convey a characteristic, we do not expect high improvement values; rather, we look for systematic shifts in the predictive accuracy. As Web Appendix C shows, there is a clear such shift, confirming the ability of the model to predict brand characteristics from color. Comparing Instagram to Flickr (the two can be compared directly, since the same binary classifier is trained for both), the model shows higher predictive accuracy for Instagram.

The ultimate performance test for BRACE (combining module1 and module 2 together) is the consumer perception of the resulting palettes. As we show next, the collage dataset yields the strongest performance in terms of consumer perception.

Resulting Palettes, Validation, and Comparison

Figure 6 presents the top 5 colors of palettes generated by BRACE for 9 different combinations of brand characteristics, trained on the collage dataset. The color set in Fig. 6a displays the suggested colors for a brand that seeks to be perceived as Charming, Feminine, and Glamorous. It contains the pink shades that are associated with femininity per the color literature (Tham et al. 2020). As we show later, the teal (fourth color from left) is also positively associated with Feminine. The beige and gray add harmony: pink is at the bottom left of the color wheel, and teal is on the bottom right (Fig. 4). Beige balances them out, creating triadic harmony.

Fig. 6b depicts the color palette for a brand positioned as Charming and not Young. Compared to Fig. 6a, the pink associated with Charming is retained, and green and brown, which as we will later see, are negatively associated with Young, appear. Pink, brown, and green form a right triangle on the color wheel, which is not harmonious. The blues balance them out by completing the square on the color wheel, creating tetradic harmony (Fig. 4). As we also show later, these specific blue shades are neither positively nor negatively associated with Charming or Young.

Figure 6: Brand colors for several combinations of brand attributes, generated by BRACE

In Fig. 6c the brand is still not Young, but now seeks to be perceived as Masculine, Cool and Tough. The green and brown from 6b are retained, ensuring not Young, but pink that is negatively associated with Masculine and Tough is replaced by mint and blue which, as we later demonstrate, are associated with Cool. Although brown and green are typically not considered Cool, their negative association with Young, and their neutrality with respect to Masculine and Tough, outweigh their negative association with Cool. Interestingly, when the not Young constraint is removed (Fig. 6d), and Outdoorsy is added, brown is no longer part of the palette, and blue shades become more dominant, as they are associated (we will show later) with Masculine, Cool and Tough. This color set exemplifies monochromatic color harmony.

Validation

We present three validation studies, assessing whether consumers can successfully identify the characteristics represented by its palettes. Studies 1 and 2 were performed on palettes generated on the digital collages set, and Study 3 compares performance across the three training sets.

Throughout the studies we evaluate palettes in three levels of difficulty – easy, medium and hard. The difficulty of a combination is determined by how consistent are its characteristics. For example, capturing Feminine and Glamorous in a single palette is easier than Small Town and Trendy. We used Aaker (1997) personality factors and facets to categorize combinations into the difficulty levels. The easy group includes combinations belonging to the same facet (e.g., Spirited and Young). The medium consists of characteristics from different facets within the same factor (e.g., Cheerful, Down to Earth, Family Oriented). The hard level consists of characteristics selected irrespective of their facet or factor (e.g., Outdoorsy and Dynamic).

Study 1. We formed random combinations of 2-4 characteristics (like those of Fig. 6) and generated palettes that reflect these characteristics at high levels (4–5): 20 from the easy, 20 from the medium, and 23 from the hard group. For each combination, we also generated palettes that represent low levels (1–2) of the same characteristics. Participants were asked to choose which of the two palettes better represents the combination ("Consider a brand that seeks to be perceived as Outdoorsy and Rugged. Which of the following palettes is the best fit?"). Note, that this is a conservative test since respondents viewed only abstract color bars without logos, imagery, or textual cues, that are key elements to forming a brand visual identity. Therefore, any recognition rate above chance can be attributed to color alone.

The average hit rate was 81% (84% for easy, 83% for medium, and 76% for hard). In all the combinations, the hit rate was above the 50% chance level, and 50 out of the 63 (79%) were statistically significant at $p < 0.05$. Detailed results are presented in Web Appendix D, Study 1. This confirms that indeed, BRACE palettes convey brand characteristics.

Study 2: We created a more challenging task, and asked respondents to compare a subset of these palettes against randomly generated palettes using the same task structure as Study 1 (Web

Appendix D, Study 2). Across 25 comparison pairs, chosen randomly to span the 3 difficulty levels, participants significantly preferred BRACE palettes in 88% of the cases. This result further confirms that respondents truly connect the brand characteristics with colors and do not merely respond to arbitrary color sets.

Training Data Comparisons

To assess the sensitivity of BRACE to training data, we conducted Study 3. We randomly selected a subset of 20 combinations (across all difficulty groups) created palettes for these combinations on the three datasets: Flickr, Instagram, and the collages (Web Appendix D, Study 3). We presented respondents with a pair of palettes per combination: either the palette trained on the collage vs. Flickr dataset, or the collage vs. Instagram. They were asked to choose which palette best represents the combination. For 85% of the palettes, respondents chose palettes resulted from the collage dataset as better representing the combination.

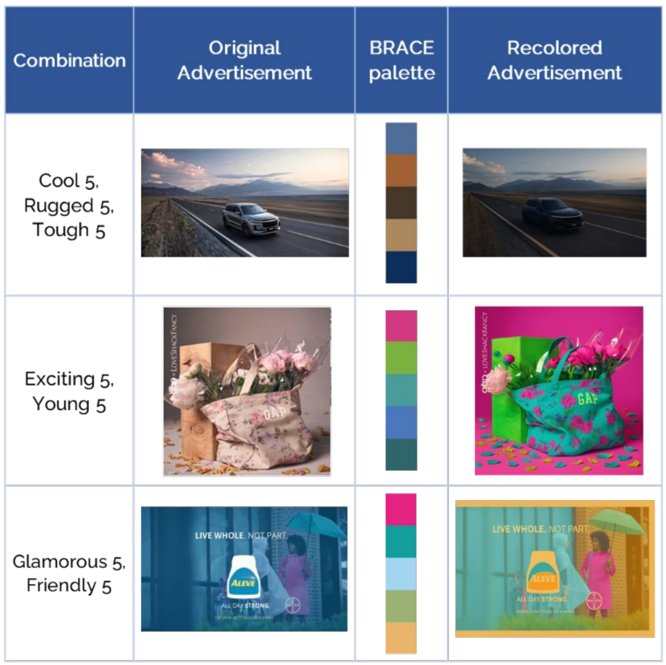
Affecting Brand Perception Through Color

Color is only one element among many that shape brand image. To test whether color alone can make a meaningful shift of consumers' perceptions, we conducted an experiment, in which we modified color palettes of real brand advertisements, replacing the original colors with palettes generated by BRACE. We find a significant shift in perceived brand characteristics. Remarkably, the effect emerges even after exposure to a single ad. The fact that the original advertisements were designed by leading brands with substantial budgets and expert creative teams indicates the power of BRACE to improve the alignment between visuals and intended brand characteristics even beyond already high-quality executions. The full details are in Web Appendix E.

Stimuli. We selected 8 brands: food and dining (Hersheys), health (Aleve), beauty (Degree), clothing (GAP), home design (Bork), beverages (Reka), department stores (Sainsbury), and cars

(Lixiang). We stratified the brands by familiarity: four brands are familiar to the average U.S. consumer (Hersheys, Aleve, Degree, GAP), and four are unfamiliar (Bork, Reka, Sainsbury, Lixiang). For each brand, we found an existing recent advertisement, prioritizing ads that contain visual elements rather than text, and minimal facial expressions.

Figure 7: Examples of original ads, BRACE palettes they were matched with, and recolored ads



We randomly selected combinations and their corresponding palettes from validation studies 1 and 2. Each ad is matched to a random and recolored in that palette, retaining all other visual attributes, including content, layout, and object proportions. Each ad was recolored using a standardized GPT-4.5 (OpenAI, 2025) prompt: *"Reproduce the original advertisement using only the colors from the provided palette. Maintain all non-color aspects of the image (composition, objects, layout, and typography) unchanged. Preserve the original image dimensions and resolution. Replace existing colors exclusively with those from the specified palette"*. See Figure 7 for examples of the original and recolored ads.

Study design: The study follows a between-subjects design. Each participant viewed eight advertisements, one per brand. For each brand, the participant was randomly assigned to either the original version (control) or the recolored BRACE version (treatment). They are then asked to rate the brand on the target characteristics on a 7-point Likert scale. The study was run on 59 Prolific respondents, paid $1.2 each.

Results: To test the hypothesis that recoloring ads using BRACE palettes alters brand perception, we estimate a linear mixed-effects model of the form:

$$(4) \quad Rating_{ijk} = \beta_0 + \beta_1 I_{ijk}^{colored} + \gamma_j\left(Brand_j\right) + \delta_k(Trait_k) + u_i + \varepsilon_{ijk},$$

where $Rating_{ijk}$ is the rating given by respondent i for brand j on brand characteristic k, $I_{ijk}^{colored}$ is a binary indicator equal to 1 for the recolored ads and 0 for the original, γ_j and δ_k are fixed effects controlling for systematic differences across brands and characteristics, and $u_i \sim \mathcal{N}(0, \sigma_u^2)$ is a respondent-specific random intercept capturing individual differences in overall rating levels. This specification estimates the effect of recoloring across all brand–trait combinations, controlling for respondent, brand, and brand personality heterogeneity.

The findings support our hypothesis. Recolored ads receive significantly higher ratings than their original versions: $\beta_1 = 0.20$, 95% CI [0.10, 0.30], $p < 0.0001$. The positive coefficient indicates that recoloring indeed increases the perceived alignment of ads with target characteristics.

Category Specific Palettes

Color combinations may elicit different response depending on product category. Palette for an Innovative and Friendly beauty brand may not be a good fit for an Innovative and Friendly financial services brand. While a full exploration of category–color relationships is beyond the scope of this paper, we extend BRACE, as a proof-of-concept, to adapt to product categories.

The extension incorporates a category-fit component into the optimization. We train 9 additional XGBoost models $f_{cat}(v_m)$, one for each category, which predict whether a palette aligns with that category. The target variable is a binary 0/1 indicator denoting whether the image comes from a brand in that category. Note that this is only possible when the images in the training data are brand related, rather than images labeled with the characteristic only. We use a regression framework that outputs a continuous score, which serves as a proxy for a palette's degree of category fit. The models are trained with 10-fold cross-validation, using 100 estimators, a maximum tree depth of 5, a learning rate of η=0.01, and a gamma value of 0.2. The out-of-sample R^2 values are: Food and dining 0.07, Beauty products 0.04, Beverages 0.04, Cars 0.04, the other 5 had an R^2 less than 0.01 due to a small number of brands and perhaps no clear color pattern. Hence, we use these four.

Figure 8: Category specific color palettes

	Family Oriented 5, Cool 4, Small Town 5	Cheerful 5, Imaginative 5, Spirited 5	Entire Category
Beauty			
Beverages			
Cars			
Food & Dining			
Not category specific			

Figure 8 presents the resulting category-specific palettes trained on the collage dataset, for Cheerful 5, Imaginative 5, Spirited 5 (Fig. 6e) and Family Oriented 5, Cool 4, Small Town 5 (Fig. 6i), across the four categories. Fig. 8 also presents palettes generated solely from the category models, without incorporating characteristics or harmony constraints (e.g., what will best predict a beauty product?). The palettes show variation across categories. Although individual color interpretations should not be overemphasized we see that category-only palettes capture broad visual tendencies of the category, such as pinks and whites in beauty or saturated primary colors in beverages. When BRACE combines category and characteristics, these category signals remain visible while adapting toward the relevant characteristics. For example, beauty palettes retain pink and white across both characteristic sets, while beverage palettes maintain vibrant saturated hues.

To validate the category-specific palettes, we followed the procedure of Study 1 and asked respondents to match palettes with a set of characteristics for a product category ("Consider a beauty brand that seeks to be perceived as Outdoorsy and Rugged. Which of the following palettes is the best fit?"). We selected 7 combinations across all difficulty groups, and created category-specific palettes for each of the four categories. Respondents were shown pairs of palettes corresponding to the same characteristic combination. One palette was generated for the focal product category, and the other for a different category. Each respondent evaluated 7 pairs of palettes. We recruited 87 Prolific respondents, each paid $1. We find that across all categories, participants correctly identified the category palette in 64.2% of cases (N=609 judgments from 87 respondents, $p = 2.27 \cdot 10^{-12}$). At the category level, accuracy is: beauty (63.6%, $p = 0.0009$), beverage (58.3%, $p=0.045$), car (68.1%, $p=2.5 \cdot 10^{-5}$), and food (67.1%, $p=1.7 \cdot 10^{-5}$). This result indicates that color perception depends on both brand characteristics and product category, highlighting BRACE's potential for research and practice in category-specific branding.

Interpreting Characteristic–Color Relationships

BRACE is valuable both managerially and methodologically. It produces palettes that align with strategic brand positioning, and its outputs are validated through consumer perception. At the same time, as with many machine-learning–based tools, some theoretical questions remain beyond its scope. What do BRACE-generated palettes imply about the underlying links between specific colors and brand characteristics? Can these links be expressed with statistical confidence, or quantified in relative strength? Existing literature documents several color–meaning relationships but does not specify which shade carries an association, how strongly, or which colors may counteract a desired characteristic. For example, yellow has been linked to Cheerfulness (Clarke and Costall 2008), but which shade of yellow, and with what magnitude? Conversely, what colors should brands avoid if they seek to appear Cheerful? BRACE integrates harmonies, multi-color interactions, and trade-offs among desired characteristics, making such relationships difficult to infer directly from the model.

Traditional interpretability tools such as SHAP values (Lundberg and Lee 2017) provide limited insight in our case, because of the high number of colors and interactions, leading to noisy and fragmented attributions. Therefore, to obtain interpretable insights about color association, we need to reduce the dimensionality. We reduce the dimensionality of the analysis along two aspects. First, we regroup the color clusters into a smaller and more interpretable set of groups. Second, we simplify the functional form by using a linear regression framework that allows us to examine directional relationships and introduce statistical controls.

Simply reducing the number of clusters with a coarser K-means does not work here: geometric clustering ignores how colors co-occur in brand images and therefore does not capture meaningful semantic relationships. Instead, a reduction method must reflect both visual similarity and how colors jointly appear in brand representations.

To achieve this, we apply Latent Dirichlet Allocation (LDA) topic modeling to the color space. Originally developed for text analysis, LDA is designed to uncover latent structure in high-dimensional data (Blei, Ng, and Jordan 2003) and is widely used in marketing and social science to extract meaningful themes from consumer datasets (Grimmer 2010; DiMaggio, Nag, and Blei 2013; Liu and Toubia 2018; Zhong and Schweidel 2020). Here, we adapt LDA to group colors. Rather than dividing the space by geometric proximity, LDA learns co-occurrence patterns, grouping colors that tend to appear together into topics. Each topic is a distribution over colors, and each image is represented by a sparse mix of topics.

A key advantage of LDA is the use of Dirichlet priors, which encourages sparsity in topic assignments. The resulting topics are distinct and minimally overlapping, and each image loads heavily on only a few topics. Such sparse, non-redundant groups are well suited for regression analysis, because they behave as nearly independent predictors. Unlike traditional clustering methods that assign colors based on proximity in color space, LDA captures how colors co-occur within brand imagery, identifying groups that reflect both visual similarity and contextual usage.

We applied LDA to the collage dataset and obtained 16 color topics (see Web Appendix F). Since each collage is also rated by the respondent on 47 brand characteristics, we regress each characteristic on the LDA weights of the 16 topics. For each characteristic, the dependent variable $y_i - \bar{y}$ is the respondent's rating (1–5), demeaned by its sample mean, and the independent variables w_{ij} are the weight of LDA topic j in collage i. We estimate 47 regressions, each with 16 predictors and 3,937 observations, we accounted for multiple comparisons using placebo permutation correction of the p-values (Abadie and Gardeazabal 2003).

$$y_i - \bar{y} = \beta_1 * w_{i1} + \ldots + \beta_{16} * w_{i16} + \varepsilon_i. \tag{4}$$

Table 2 presents the results. Rows correspond to brand characteristics and columns to color topics. The coefficients represent direction and strength of association; significant coefficients (5% and 1%) are highlighted. For example, Family Oriented is positively associated with topics 6 and 15 (green palettes) and topic 13 (warm yellow), while topic 16 is positively associated with Western and Small Town and negatively associated with Confident and Cool.

Table 2 shows face validity, is consistent with the literature of Fig. 2, and also extends the literature by discovering additional relationships. Consistent with the literature, topic 8, dominated by shades of pink, is positively associated with Feminine. Topics 6 and 15, dominated by greens, are positively associated with Outdoorsy (which is related to nature). Topic 13, with shades of yellow, is positively associated with Cheerful, again consistent with prior research. We also discover new relationships. For example, green-dominated topics 6 and 15 are positively related to Down to Earth, Family Oriented, and Wholesome, and negatively related to Cool, Glamorous, and Trendy. While prior studies generally link pink to Femininity and Romance (Clarke and Costall 2008; Cerrato 2012; Tham et al. 2020), the pink-dominated topic 8 has broader meaning. It is positively associated not only with feminine traits (Feminine, Charming, Glamorous) but also with Confident, High Quality, Imaginative, Intelligent, Successful, and Trendy, and negatively associated with stereotypically masculine characteristics such as Tough, Rugged, and Western.

Although one should avoid assigning overly precise interpretations to machine-learning outputs, the characteristic–color relationships revealed by our topic analysis provide useful intuition for BRACE-generated palettes. In Fig. 6a, the pink shades (topic 8) align with Feminine, Charming, and Glamorous, and teal tones (topic 1) reinforce Feminine. In Fig. 6b (Charming and not Young), BRACE favors colors resembling topics 5 and 16 (yellows and browns), which are negatively associated with Young, and avoids pink tones, which, however Charming, would signal youth. In Fig. 6c, purple-blue tones from topic 12 appear, consistent with Masculine, Cool, and Tough, while pink (associated with not Tough) is absent. The palette for Family Oriented, Cool, and Small Town (Fig. 6i) has greens and blues (topics 15 and 16) and avoids purple and pink (topics 8 and 12), which are negatively associated with Family Oriented and Small Town.

An important theoretical question concerns the independence of color associations. To what extent do they reflect the colors of objects or scenes that appear in collages (e.g., blue may derive from water motifs common in beauty brands), versus operating symbolically, independent of context? To examine this, we reran the regressions with controls for the 20 most frequent image-content topics (Web Appendix G). For most characteristic-color pairs, the coefficients remained significant. For example, Cool remains positively associated with the purple topic 12 with or without content controls. However, Charming's positive link to the pink topic 8 disappears after controlling for content, and the coefficients of flowers and baking become significant, suggesting that pink's association with Charming is largely driven by certain pink objects.

Together, these analyses provide two complementary layers. Web Appendix G clarifies when associations originate from objects rather than from colors themselves, offering insight into the symbolic versus contextual drivers of brand color meaning. However, for managerial decision making, color choices are agnostic to where the associations originate from, and the main effect of characteristic–color relationships in Table 2 should be used. For example, if a brand wishes to be perceived as Tough, it should not use the pink-dominated topic 8, irrespective whether this negative association comes from flowers, baking, or higher-level intrinsic meaning. If it wants to be perceived as Cool, the Cool perception of purple topic 12 remains even without purple objects.

Table 2: Coefficients of the characteristic-color regression (Eq. 4)

Characteristic	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Charming	0.09	(0.12)	(0.01)	(0.32)	(0.10)	(0.05)	0.27	0.55	0.08	0.05	(0.18)	0.28	0.11	(0.36)	0.12	(0.02)
Cheerful	0.01	0.07	(0.28)	(0.25)	(0.10)	0.11	0.45	0.16	0.23	(0.22)	0.08	0.15	0.53	(0.06)	0.16	(0.34)
Confident	0.16	(0.01)	(0.09)	0.05	0.06	(0.14)	(0.03)	0.35	0.02	0.13	0.02	0.37	(0.01)	(0.32)	(0.25)	(0.10)
Contemporary	0.12	(0.02)	(0.14)	(0.30)	0.06	(0.09)	(0.10)	0.27	(0.23)	0.23	0.01	0.31	(0.28)	0.20	(0.20)	0.13
Cool	0.31	(0.15)	0.18	(0.13)	(0.16)	(0.35)	0.50	0.23	0.16	0.38	(0.00)	1.02	(0.20)	(0.32)	(0.33)	(0.34)
Corporate	0.02	(0.09)	(0.14)	(0.05)	(0.28)	0.07	(0.38)	(0.05)	0.18	0.17	(0.04)	0.15	(0.18)	0.47	(0.08)	0.23
Daring	0.00	0.13	0.13	0.14	(0.15)	(0.17)	(0.09)	(0.27)	(0.08)	0.32	0.03	0.65	(0.38)	0.09	(0.65)	0.13
Different	0.07	0.03	(0.21)	(0.20)	(0.20)	(0.14)	0.09	0.23	0.05	0.32	(0.19)	0.48	(0.38)	0.38	(0.10)	0.01
Distinctive	0.06	(0.11)	0.07	(0.17)	(0.27)	(0.18)	0.21	0.13	0.06	0.05	(0.06)	0.57	(0.15)	0.61	(0.10)	(0.08)
Down to Earth	(0.03)	0.21	0.14	(0.00)	(0.03)	0.25	(0.09)	(0.12)	(0.60)	(0.31)	(0.13)	(0.36)	0.22	(0.29)	0.31	0.05
Dynamic	(0.10)	(0.07)	0.22	(0.06)	(0.12)	(0.23)	0.22	0.21	0.01	0.04	0.01	0.54	(0.11)	0.28	(0.15)	(0.12)
Exciting	0.20	0.02	(0.12)	(0.08)	(0.13)	(0.24)	0.48	(0.04)	0.39	0.41	0.05	0.59	(0.31)	(0.12)	(0.34)	(0.23)
Family Oriented	(0.09)	(0.10)	(0.46)	(0.24)	0.00	0.40	0.09	(0.47)	(0.39)	(0.01)	0.07	(0.69)	0.81	0.13	0.59	0.14
Feminine	0.55	0.16	(0.57)	(0.23)	(0.13)	0.03	(0.24)	1.40	(0.37)	(0.06)	(0.38)	0.01	(0.36)	(0.19)	0.17	(0.12)
Friendly	0.11	0.02	(0.11)	(0.27)	0.07	0.18	0.11	0.08	(0.13)	(0.09)	0.12	(0.30)	0.48	0.03	0.20	(0.27)
Glamorous	0.09	(0.08)	(0.27)	(0.20)	(0.35)	(0.28)	(0.22)	0.70	0.13	0.67	(0.23)	1.08	(0.73)	0.20	0.01	(0.07)
Good Looking	0.13	(0.16)	(0.13)	0.01	(0.13)	(0.10)	0.08	0.61	0.18	0.31	(0.14)	0.53	(0.07)	(0.15)	(0.07)	(0.29)
Hardworking	0.16	(0.19)	0.23	0.10	0.06	0.13	(0.34)	0.02	(0.04)	(0.12)	(0.01)	0.12	(0.08)	(0.02)	(0.14)	0.00
High Quality	(0.04)	(0.13)	(0.08)	0.27	0.17	(0.18)	0.15	0.47	(0.27)	0.30	(0.43)	0.31	0.07	(0.32)	0.18	(0.23)
Honest	0.17	(0.09)	(0.02)	(0.03)	0.09	0.06	(0.04)	0.23	(0.01)	(0.16)	(0.24)	(0.10)	0.04	(0.06)	0.27	(0.09)
Imaginative	0.08	(0.05)	(0.06)	(0.31)	0.15	(0.07)	0.10	0.38	0.56	0.07	(0.15)	0.50	(0.22)	0.05	(0.25)	(0.12)
Independent	0.04	(0.10)	(0.11)	0.03	0.14	(0.08)	0.18	0.21	0.10	0.22	(0.08)	0.42	(0.31)	(0.01)	(0.36)	(0.05)
Innovative	0.08	(0.25)	(0.17)	(0.06)	(0.07)	(0.10)	0.05	0.28	0.29	0.25	0.07	0.32	(0.11)	0.05	(0.29)	0.12
Intelligent	0.18	(0.12)	0.06	(0.08)	0.12	(0.09)	(0.22)	0.39	(0.13)	0.08	(0.05)	0.29	(0.13)	0.19	(0.21)	(0.08)
Leader	0.07	0.08	0.18	(0.06)	(0.08)	(0.12)	0.29	0.08	(0.02)	0.22	(0.21)	0.35	(0.10)	(0.09)	(0.18)	(0.20)
Masculine	(0.20)	(0.02)	0.45	0.44	0.10	(0.10)	0.10	(0.95)	0.05	0.38	(0.24)	0.66	(0.77)	(0.08)	(0.49)	0.20
Original	0.17	(0.08)	(0.09)	(0.09)	0.04	(0.07)	0.12	0.22	0.04	0.10	(0.14)	0.11	(0.13)	0.15	(0.12)	(0.02)
Outdoorsy	0.06	(0.38)	0.58	0.44	(0.32)	0.28	0.31	(0.87)	(0.30)	(0.06)	0.16	(0.07)	(0.36)	(0.43)	0.51	(0.10)
Real	0.04	0.01	(0.24)	0.06	0.23	0.15	(0.07)	0.00	(0.04)	0.03	(0.22)	(0.06)	0.14	(0.03)	0.07	(0.12)
Reliable	0.22	(0.09)	(0.05)	0.07	0.05	(0.00)	0.01	0.17	(0.08)	0.08	(0.06)	(0.21)	0.11	(0.13)	0.22	(0.23)
Rugged	0.08	(0.20)	0.62	0.60	0.01	(0.10)	(0.05)	(0.88)	(0.52)	0.18	(0.15)	(0.20)	(0.70)	0.09	(0.02)	0.26
Secure	0.08	(0.10)	(0.05)	(0.14)	0.25	0.04	0.16	0.24	(0.39)	0.13	(0.07)	(0.06)	0.04	(0.09)	(0.03)	(0.08)
Sentimental	0.01	0.12	(0.17)	(0.00)	0.19	(0.01)	(0.03)	0.41	(0.54)	(0.12)	(0.23)	(0.35)	0.11	0.09	0.12	0.05
Sincere	(0.07)	0.04	(0.11)	(0.17)	(0.10)	0.18	0.02	0.23	(0.07)	0.15	(0.24)	(0.22)	0.23	0.13	0.25	(0.16)
Small Town	(0.19)	0.17	0.45	0.06	0.01	0.29	(0.19)	(0.64)	(0.31)	(0.35)	0.01	(0.92)	(0.05)	(0.31)	0.17	0.50
Smooth	0.23	(0.17)	(0.14)	0.18	(0.11)	(0.07)	(0.09)	0.52	0.15	0.37	(0.35)	0.57	(0.12)	(0.42)	0.05	(0.27)
Spirited	0.05	0.02	0.00	(0.19)	(0.15)	(0.11)	0.26	0.04	0.20	0.18	(0.12)	0.91	0.14	(0.23)	(0.11)	(0.26)
Successful	0.12	0.02	(0.13)	0.13	(0.03)	(0.12)	0.14	0.31	0.09	0.06	(0.14)	0.13	(0.03)	(0.16)	(0.04)	(0.17)
Technical	0.08	(0.29)	(0.01)	0.22	(0.27)	(0.14)	(0.35)	0.23	(0.09)	0.19	(0.35)	0.67	(0.28)	0.20	(0.14)	0.32
Tough	0.19	0.06	0.41	0.47	0.04	(0.19)	(0.11)	(0.67)	(0.33)	0.26	0.06	0.12	(0.56)	(0.25)	(0.36)	0.08
Trendy	0.24	(0.11)	(0.22)	(0.26)	(0.03)	(0.28)	0.30	0.38	0.61	0.44	(0.35)	0.88	(0.18)	0.16	(0.42)	(0.15)
Unique	0.10	(0.05)	(0.32)	0.04	0.04	(0.16)	0.25	0.31	0.32	0.11	(0.13)	0.48	(0.28)	0.07	(0.26)	(0.07)
Up to Date	0.14	(0.01)	(0.05)	0.01	(0.08)	(0.06)	0.05	0.12	0.13	0.48	(0.22)	0.48	(0.08)	(0.02)	(0.36)	(0.21)
Upper Class	0.19	(0.16)	(0.08)	0.09	(0.30)	(0.13)	(0.28)	0.29	0.06	0.55	(0.03)	0.82	(0.24)	(0.40)	(0.08)	(0.10)
Western	(0.18)	(0.12)	0.08	0.19	(0.49)	0.06	0.17	(0.51)	(0.26)	0.02	(0.08)	0.14	0.01	0.29	(0.04)	0.41
Wholesome	0.01	(0.14)	(0.17)	(0.06)	0.07	0.29	(0.12)	0.22	(0.30)	(0.24)	(0.11)	(0.40)	0.44	(0.13)	0.47	(0.01)
Young	0.36	0.03	0.01	(0.27)	(0.01)	(0.00)	0.50	0.32	0.45	(0.05)	(0.06)	0.35	0.13	(0.22)	(0.38)	(0.41)

Light blue: $p<0.05$; Dark blue: $p<0.01$

Discussion

This research advances the study of brand visual communication by moving beyond isolated color effects toward a systematic, scalable approach to color palette design. Managerial practice largely relies on general design rules, aesthetic intuition, and iterative AB testing. Academic research focused on a limited set of individual colors, rarely addressing color palettes and combinations of characteristics. In contrast, our approach operates over the full color spectrum, incorporates shades and multi-color combinations, allows brands to balance multiple, sometimes competing, characteristics, and accounts for harmony constraints and category context. It provides a structured way to navigate the almost infinite space of possible palettes in a manner that is both theoretically grounded and empirically validated.

The framework has already proven useful in practice. For example, 888 Holdings, a world-leading online gaming company, considered changing its signature green logo in an effort to appear more modern and updated. After analyzing brand collages for 888 and its nine major competitors in the UK, we found that green emerged as a dominant and differentiating color in consumers' visual representations. Importantly, the color reflected associations such as Family Oriented, which are not typically emphasized in gaming but carried positive connotations among its users. Based on these insights, the company decided to retain the green in its rebranding.

The research also opens several avenues for future work. One direction is to study how color–perception relationships evolve over time, particularly as cultural trends shift. For example, black has recently become prominent in brand communications (e.g., Apple, Chanel, HBO). One may wander what would be the effect of this trend on the perception of black. A second direction concerns color strategies in brand extensions, examining which palette elements should transfer from the parent brand and which should adapt. A third avenue involves competitive differentiation, exploring how brands can use color palettes to stand out more effectively in crowded categories. The ability to purposefully design color palettes that align with strategic goals offers firms a powerful new way to communicate who they are and who they aspire to be.

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