

## We Look Like What We Like

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## ABSTRACT

Our faces are said to be windows into the soul. But can they also reflect who we are as consumers? Can facial images predict brand preferences? To answer these questions, we analyze a unique dataset of over 100,000 single-face Twitter profile pictures linked with brand followership data for 444 brands across categories and brand personality metrics. Using advanced machine learning for automated face analysis, we demonstrate that consumers' social media profile faces can reveal their preferences between rival brands (study 1). We further show that consumers who follow brands with similar brand personality traits (e.g., glamorous, rugged) tend to look alike (study 2). Finally, we identify facial appearance characteristics associated with brand personality traits; for example, followers of "smart" brands like Barnes & Noble are likely to wear reading glasses, while "edgy" brands like Diesel attract bearded men (study 3). Together, our findings show that brands can extract actionable insights from consumers' facial images, both to address the "cold start" problem by predicting preferences before any consumption actions are observed and to better understand the brand's identity through the aggregated traits of its followers. This work is among the first to demonstrate large-scale associations between faces and brand preferences.

*Keywords:* face analysis, deep learning, brand preferences, social media mining

One of the first impressions a person makes about another in an offline or online environment is based on their physical appearance and particularly their face (Todorov 2017; Willis and Todorov 2006). In the online environment this is often manifested by the face users display in their profile pictures on social media platforms. In this research, we explore the marketing value of this important source of information—faces. Specifically, we examine whether a consumer’s social media face can reveal their brand preferences.

For decades, researchers have been fascinated by the information contained in faces (Zebrowitz 1997). Faces displayed on social media profile pages have already been successfully used to predict personal characteristics such as social tags like names (Zwebner et al. 2017, 2024), political affiliation (Kosinski 2021; Tkachenko and Jedidi 2023), personality traits (Segalin et al. 2017), job fit (Troncoso and Luo 2023), and arguably even sexual orientation (Wang and Kosinski 2018). Building on this body of research, we address a novel and managerially relevant question: Can consumers’ brand preferences be inferred from their facial appearance?

We introduce the concept of “brand faces,” examining the association between consumers’ facial appearance and their brand preferences. Specifically, we propose that there is a systematic link between consumers’ preferred brands and their social media profile faces, such that their preferred brands can be inferred from their facial appearance. This investigation not only extends existing research on identity-related inferences from faces but also highlights the potential of unstructured data in marketing applications.

To illustrate our goal, consider for example the popular “Get a Mac” ad campaign, which presented two consumers: one who “looks” like a *Microsoft* customer and another who “looks” like an *Apple* customer (see figure 1A for an image from the ad). The visual difference between

the two is salient, representing each brand’s “typical” customer and aligning with the brand’s personalities (i.e., intelligent, and geeky for Microsoft vs. fun and cool for Apple). Although the ad presents full-body images of the figures, even their faces alone (see figure 1B) communicate this distinction. In a pilot study, we found that people could accurately choose which face represents which brand ( $N = 181; p < .001$ ).<sup>1</sup> While the “Get a Mac” marketers maximized the distinction between the models in the ad, and it is possible that some respondents were familiar with the ad, we also find differences in the profile images of real Apple versus Microsoft brand followers on Twitter<sup>2</sup>. Specifically, we find that we can predict, significantly better than chance, which users follow Microsoft versus Apple based solely on their facial profile images ( $M_{\text{accuracy}} = 0.582, SD = .058; p < .001$ ). This example suggests that brand-related characteristics can be inferred from facial images motivating our investigation into whether faces convey meaningful information about consumers’ brand preferences and whether marketing-related insights can be extracted from online facial images.

## FIGURE 1

### ILLUSTRATIVE EXAMPLE: FACES AS A RICH SOURCE OF INFORMATION

#### FIGURE 1A

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<sup>1</sup> For illustration, we ran a pilot study ( $N = 181$ ; Universality Lab) in which participants were presented with a “Mac face” and a “PC face,” shown sequentially on separate screens (order randomized). After viewing each face, participants were asked whether the person in the picture prefers a Mac or a PC. Accuracy was high for both the Mac face (75.7%) and the PC face (72.9%). To provide a conservative benchmark, we focus on responses to the first face viewed: 71.8% of participants correctly identified the depicted person’s preferred brand, significantly above the 50% chance level ( $t(180) = 6.51, p < .001$ ).

<sup>2</sup> Throughout this article we refer to the platform  $X$  (formerly *Twitter*) as *Twitter* since we collected the data at the time it was called Twitter.



**FIGURE 1B**



*Note.* Source: [https://www.youtube.com/watch?v=qfv6Ah\\_MVJU](https://www.youtube.com/watch?v=qfv6Ah_MVJU)

Social media platforms are characterized by a long tail, where most consumers are fairly inactive on the platform (Pew Research Center, 2019; Pew Research Center 2022). Nonetheless, even relatively inactive users can provide a rich set of observable cues when they choose to share a profile picture. Consumers' faces provide a wide variety of information, ranging from demographic attributes like gender and age to intentionally chosen characteristics such as accessories (e.g., reading glasses, makeup, hair cues, or a beard) and emotions expressed through facial expressions (happiness, sadness, or anger, etc.; Ekman 1999). The ability to infer such characteristics and signals from facial images alone offers valuable opportunities for understanding consumer identities, preferences, and behaviors even when activity data are sparse.

To examine this potential, we leverage a large-scale dataset of Twitter users' profile images and their brand followership. Using advanced machine learning techniques, we (1) predict brand followership from facial appearance alone (study 1), (2) examine how brand similarity explains classification success by linking brand personality to face similarities (study 2), and (3) identify specific facial characteristics associated with different brand "personalities" (study 3). Across all studies, we control for age and gender to ensure that our findings are not driven by basic demographic differences. This approach allows us to test whether faces convey meaningful information about brand followership and preferences.

Specifically, our findings in study 1 reveal that individuals' social media profile faces can reliably predict their brand preferences, even when controlling for inferred demographic attributes, namely age and gender.<sup>3</sup> For example, based on facial appearance alone, we can predict whether someone is more likely to eat at KFC or Chick-Fil-A, drink Miller Lite or Bud Light, watch NBC or CNN, drive an Audi or a Mercedes Benz, or shop at Walmart or Target.

In study 2, we tested whether brands with similar personality characteristics (based on Brand Asset Valuator (BAV) data) are followed by consumers with similar facial appearance characteristics. We found that the more two competing brands resemble each other in terms of personality characteristics, the less informative facial appearance becomes for distinguishing between their followers. Put differently, brands with overlapping personalities tend to attract consumers who not only share preferences but also resemble each other—reflecting the adage that birds of a feather flock together.

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<sup>3</sup> We use brand followership on Twitter as a proxy for brand preferences, but we acknowledge that some consumers may follow a brand for other reasons such as employment at the company. We rely on previous research (Culotta and Cutler 2016; Schoenmueller et al. 2023) that demonstrated the relationship between Twitter followership and brand preferences.

Finally, in study 3, we examined the relationship between specific facial appearance characteristics and brand personalities (i.e., BAV data). For example, followers of “smart” brands are more likely to wear reading glasses and use less makeup, while “edgy” brands attract younger, bearded men. “Adventurous” brands are associated with happier men’s faces featuring prominent sideburns. Within categories, we also identified distinctive patterns: men following Mercedes tend to be balder, Tesla followers appear happier, Volvo has the highest proportion of blond-haired women followers, and Tesla has the highest share of gray-haired men. These findings reveal how facial cues align with brand identities, offering new insights into how consumers signal identity through both their appearance and brand affiliations.

Our work offers theoretical, managerial, and methodological contributions to the marketing literature. Theoretically, to the best of our knowledge, this is the first work to systematically relate facial cues from social media profile faces to brand followership, establishing an association between facial appearance and brand preferences. Furthermore, it advances theories on brand personality by showing that the facial cues of potential brand consumers can correlate with brand personality characteristics and by identifying specific facial characteristics that represent different brand personalities.

Managerially, our work has important implications for marketers and firms, offering a method to analyze the facial appearances of social media followers at scale using machine learning to better understand consumer characteristics and identify potential users aligned with their brand. This approach enables firms to target individuals who do not yet follow the brand but share characteristics with existing followers, leveraging implicit information from users’ social media faces. By addressing the “cold start” problem – where limited data exists on consumers’ preferences or behaviors, such as purchase history or platform activity (Padilla and

Ascarza 2021)—brands can use our scalable solution to predict brand preferences and identify potential consumers based on the faces of existing consumers. For advertising, it can also guide the selection of representative consumers or the selection of consumer features such as accessories for ad creatives to potentially enhance relevance and persuasion.

Additionally, by aggregating information across individual consumers, brands can gain valuable insights into their own identity characteristics, such as perceived glamour, dominant emotional expressions like happiness, and aesthetic traits like baldness. This is possible even in the absence of direct consumer actions like posts or reviews. Social media profile pictures, much like brand choices, act as curated identity signals that combine innate physical traits with deliberate decisions (e.g., makeup, glasses, or facial hair), offering a rich data source for understanding both consumer and brand identity. These insights can inform personalized recommendations and advertising strategies.

We note, however, that it is essential for brands to address privacy concerns when analyzing profile images, even when such images are publicly available on social media. To ensure ethical use, companies should adopt transparent consent mechanisms, and both policymakers and platforms must enforce and monitor these practices to protect user privacy. To protect consumer privacy, we therefore report all our findings only at the aggregate level so that individual information cannot be identified.

## **CONSUMER FACES AND BRAND IDENTITIES**

### **The Informativeness of Facial Appearance**

There is ample evidence that morphological and social cues in a human face provide signals of human personality and behaviors (Kachur et al. 2020; Zebrowitz 2006). While some facial cues are more salient like gender and age (Montepare and Zebrowitz 1998), others are less evident and include personality traits such as trustworthiness (Cogsdill et al. 2014; Todorov et al. 2008), competence (Ballew and Todorov 2007), meanness (Cogsdill and Banaji 2015), the Big Five (Kachur et al. 2020; Segalin et al. 2017), and even identity characteristics, for example, a person's given name (Zwebner et al. 2017, 2024). In fact, faces can predict important social outcomes such as investment decisions (Todorov et al. 2015), loan repayment (Chen et al. 2023), corruptness (Hong et al. 2021), entrepreneurial emergence (Stefanidis et al. 2022), electoral success (Ballew and Todorov, 2007; Todorov et al. 2005), and sentencing criminal justice decisions (Blair, Judd, and Chapleau 2004; Eberhardt et al. 2006; Zebrowitz and McDonald 1991). To this list we add another interesting and an unexplored managerially relevant dimension—brand preference.

While research on inferences from facial appearance has traditionally focused on judgments made by social perceivers, the growing availability of online user faces and the increasing use of computational methods in recent years have opened new opportunities to examine fine-grained information conveyed by faces at a much larger scale. Such techniques allow researchers to form predictions from consumers' facial appearance as presented on their profile pictures on social media platforms (Segalin et al. 2017; Toisoul et al. 2021; Zwebner et al. 2017). Reflecting the value of this source of information, marketing scientists have started leveraging such techniques. For instance, researchers have examined the relationship between sellers' attractiveness in online profile images and product sales (Peng et al. 2020), the link between ad sharing and facial responses displayed online (McDuff and Berger 2019), and how a

host's smile in their Airbnb profile picture increases the likelihood of a booking (Zhang et al. 2025).

Building on this research linking variation in faces to marketing metrics, we aim to extract relevant facial characteristics at scale to examine the novel association between a person's facial appearance and their brand preferences. Faces convey a rich array of cues, some relatively stable (e.g., height-to-width ratio) and other malleable (e.g., makeup, growing a beard, or wearing glasses), and they also express emotions. For example, facial expressions of anger and disgust convey dominance, while fearful and sad expressions signal the opposite (Knutson 1996). Moreover, individuals are perceived as less attractive when posing with sad expressions (Mueser et al. 1984) but appear more cooperative and sociable with positive expressions (Bernstein et al. 2010).

### **Faces, Brand Preferences, and Identity Signaling**

Why might brand preferences be reflected in one's facial appearance? Brands often attract specific consumer segments and allow individuals to express their identity, values, and personality traits (Aaker 1997, 1999; Berger and Heath 2007; Bellezza and Berger 2020). In recent years, consumers have increasingly used social media to express their brand preferences, providing valuable insights for brands. For instance, Liu, Dzyabura, and Mizik (2020) analyzed aggregate brand dimensions from Instagram posts (not including consumer profile pictures), Nam, Joshi, and Kannan (2017) harvested brand information from social tags, while Dzyabura and Peres (2021) explored brand perceptions elicited from visual brand collages.

Just as individuals select specific brands to reflect and communicate aspects of their personality, they curate their online personas through profile pictures on social media, using their

faces as identity signals. For example, wearing glasses can influence perceptions of intelligence (Wei and Stillwell 2017) and suitability for jobs associated with that trait (Troncoso and Luo 2023). We propose that individuals who choose to “look” intelligent will prefer brands with an “intelligent” personality, while those who curate a glamorous looking face on their social media profile, will prefer brands with a “glamorous” personality. Building on prior research that connects facial appearance to identity, and brand preferences to identity, we propose that a consumer’s facial appearance can reflect their brand preferences throughout shared underlying identity signals.

In summary, leveraging insights from prior research on facial cues, identity signaling, and brand preferences, our study extends existing literature by proposing and empirically testing a novel link between consumers’ curated social media faces and their brand preferences. This approach offers a scalable and ecologically valid framework for understanding identity-driven consumption behaviors.

## **OVERVIEW OF STUDIES**

Properly measuring brand preferences at scale is often challenging. Brand-owned data or surveys may be biased, costly, and slow, while neutral third-party datasets often lack accuracy in reflecting consumers’ current, independent choices. Moreover, third-party data cannot connect facial appearance to brand preferences. To overcome these limitations, we leverage Twitter data, linking facial appearances from profile pictures to real-world consumer behavior, as reflected in the brands consumers choose to follow. This approach captures consumer preferences with high ecological value and enables scalable predictions of brand preferences based on facial cues at scale.

Specifically, employing deep learning techniques for automated facial analysis (Ryali et al. 2020), we examine whether facial appearance in social media profile pictures is related to consumers' brand preferences. Our dataset includes over 100,000 single-face profile images, along with each user's followership for 444 brands across more than 20 categories (e.g., apparel, cars, print media outlets) on Twitter.

Across three complementary analyses, we investigate the predictive power of facial appearance for brand followership. Using over 3,426 unique within-category brand pairs—including 'canonical rivals' such as Apple vs. Microsoft—study 1 tests whether brand followership can be predicted from facial appearance alone and finds that such predictions significantly exceed random-chance baselines, even after controlling for inferred demographics, that is, age and gender.

Study 2 examines whether brands with similar identities (e.g., glamorous brands) attract followers with similar facial appearance characteristics. We find that the closer two brands are in identity (measured by their brand personality characteristics), the less informative facial characteristics become in distinguishing their followers. That is, brands with overlapping personalities tend to attract visually similar users.

Finally, study 3 examines whether specific facial characteristics align with the personality dimensions of the brands consumers follow. Leveraging established brand personality traits from Young & Rubicam's Brand Asset Valuator (BAV) consumer-brand-perception survey, we test whether certain facial characteristics are systematically associated with these brand identities. For example, do "rugged" brands like Timberland attract followers with rugged facial features, such as sideburns? Our analysis reveals robust associations between 27 specific facial

characteristics and 47 brand personality traits: sideburns are linked to “rugged” brands, eyeglasses to “intelligent” brands, and lip and eye makeup among women to “glamorous” brands.

To address potential privacy concerns (Van Noorden 2020; Zhou et al. 2020), all results are reported at the aggregated level. No individual-level results are reported or disclosed ensuring the ethical use of publicly available profile data.

## **Data**

To investigate whether faces reveal traces of brand preferences, we used data from the social media platform Twitter, which provides a unique setting with a rich source of publicly available data at scale. This allowed us to collect information about users’ brand preferences—via the brands they follow—and their facial characteristics, as displayed in their profile pictures. For 444 brands across a comprehensive range of sectors we collected the 5,000 most recent followers and their profile picture at the time of data collection (February 2019). Out of this set of followers, we could access valid profile pictures of 122,161 Twitter users ( $M_{\text{age}} = 29.6$ ,  $SD_{\text{age}} = 10.3$ ; 48.6% women)<sup>4</sup>. Images containing multiple faces or no recognizable faces were excluded. All brands were selected from Y&R’s Brand Asset Valuator, which tracks brands highly relevant to consumers (see appendix A for the full list of categories). On average, Twitter users in our sample follow 19 brands ( $SD = 23$ ). For an example of a Twitter brand page representing a brand’s official social media presence, see appendix B.

*Twitter users’ profile pictures.* We extracted relevant information from the profile pictures of Twitter users in our sample, representing the data in a reduced and interpretable set of

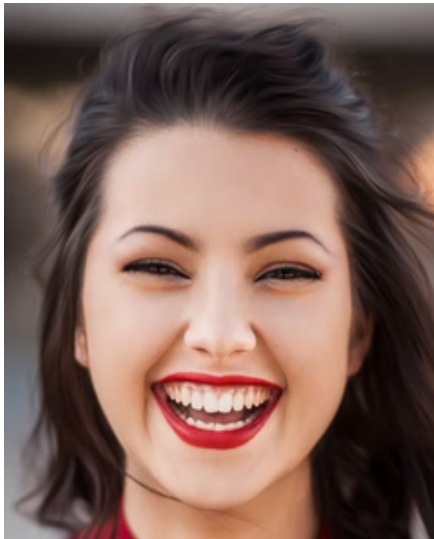
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<sup>4</sup> We describe below how we inferred and validated demographic information on the users’ age and gender.

characteristics to relate these features to brand preferences. Our goal was to encode user’s facial characteristics as efficiently as possible while retaining their distinctive traits. Instead of using the raw pixel intensities of images as input variables for a deep neural network (Witte et al. 2026), we prioritized explainability by employing specialized software (MS Azure). This software generated a low-dimensional representation of each user’s face, consisting of interpretable characteristics such as the age and emotions inferred from facial expressions (see an example in figure 2), which have been used and evaluated in prior empirical studies (Terhoerst et al. 2021; Yao et al. 2025).

## FIGURE 2

### EXAMPLE PROFILE PICTURE WITH EXEMPLARY FACIAL APPEARANCE CHARACTERISTICS

	<ul style="list-style-type: none"><li>• <b>Inferred Gender:</b> Woman</li><li>• <b>Inferred Age:</b> 26</li><li>• <b>Reading Glasses:</b> No</li><li>• <b>Sunglasses:</b> No</li><li>• <b>Emotion:</b> Happiness</li><li>• <b>Hair Color:</b> Black</li><li>• <b>Head Pitch, Roll, Yaw:</b> -2.4, 7.1, -5.6</li><li>• <b>Eye Makeup:</b> Yes</li><li>• <b>Lip Makeup:</b> Yes</li></ul>
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*Note.* For illustrative purposes, we replaced the profile picture with a comparable royalty-free image from Unsplash to be respectful of user’s privacy (Source: [https://unsplash.com/photos/mEZ3PoFGs\\_k](https://unsplash.com/photos/mEZ3PoFGs_k)). See appendix C for full list of characteristics and summary statistics across all users.

This process yielded 27 distinct facial characteristics, grouped into seven overall categories. See table 1 for a complete list of all extracted dimensions. The first category includes demographic information inferred from users' faces, such as estimated age and inferred gender, which can serve as a substitute for self-reported demographic data that is often difficult to obtain on social media. To validate the reliability of these measures, we compared the gender and age predictions from facial analysis to a subset of Twitter users ( $n = 64,837$ ) with available demographic information (i.e., gender and age) from their Twitter profile names building on approaches used in previous research (Boghrati and Berger 2023).<sup>5</sup> The results demonstrate strong positive and significant correlations for both gender ( $\rho = 0.86, p < .001$ ) and age ( $\rho = 0.25, p < .001$ ). Additionally, we compared the average inferred age of brand followers to self-reported age and gender data from the YouGov brand survey for a subset of brands ( $n = 215$ ). These comparisons also revealed reliable positive and significant correlations for both gender ( $\rho = 0.74, p < .001$ ) and age ( $\rho = 0.37, p < .001$ ). In our analysis we will treat gender and age as control variables and assess the predictability of user facial features above and beyond these demographic features.

In addition to demographic information, the remaining six categories capture a range of facial and image-level characteristics. The second category includes head pose indicators, such as pitch, roll, and yaw, which reflect the angle and orientation of the user's face in the image. The third category captures emotional expressions, including visible cues of happiness, sadness, or anger, as inferred from facial musculature. The fourth category focuses on accessories such as eyeglasses or sunglasses, that may signal aspects of identity or lifestyle. The fifth category

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<sup>5</sup> For gender prediction we used the gender guesser library (<https://pypi.org/project/gender-guesser/>), for age prediction we used the age from name library (<https://github.com/JasonKessler/agefromname>).

includes transient appearance characteristics such as make up, facial hair, and hair color, which are often deliberately chosen and can reflect aspects of self-presentation. The sixth category describes the facial structure (i.e., height-to-width ratio; Stirrat and Perrett 2012). The last category includes attributes that are not part of the facial appearance itself but nonetheless shape its perception, such as image quality (e.g., blurriness or noise).

To holistically capture the user’s self-presentation, we analyzed profile images “as-is,” taking into account elements like cosmetics, and accessories, for example, whether a user chooses to “wear a smile” or “wear sunglasses” in their profile picture. As previously discussed, we expect these self-presentation choices to relate to brand preferences.

**TABLE 1**  
OVERVIEW OF EXTRACTED DIMENSIONS

Category	Characteristics
Demographics	Inferred age, inferred gender
Head position	Face angle (pitch, roll, yaw)
Emotional expressions	Happiness, anger, contempt, disgust, fear, sadness, surprise
Accessories	Reading glasses, sunglasses
Transient features	Eye makeup, lip makeup, beard, sideburns, baldness, hair color (blond, black, gray, red)
Face shape	Height-to-width ratio
Image quality	Exposure, blur, noise

*Note.* Features were extracted from users’ Twitter profile images using automated facial analysis.

*Twitter users’ brand followership.* On Twitter, brands maintain official accounts to share content and engage with interested users. Twitter users can choose to follow these brand accounts, enabling them to receive updates about new products, advertising campaigns, or brand-

related events directly in their feed. As such, brand followership on Twitter can be assumed to indicate a user's interest in the brand and can serve as a proxy for brand preference.

However, we acknowledge that brand followership may sometimes reflect motivations other than preference. For example, employment at the company, general interest in the product category, or social reasons. To improve the validity of our measure, we restricted our within-category brand-pair comparisons to users who exclusively followed one of the two competing brands (an average of 10.1% follower overlap between two brands within a category). This restriction reduces the influence of alternative explanations, such as a general category interest (Schoenmueller, Netzer, and Stahl 2023).

Before we turn to assessing whether facial characteristics of brand followers predict brand preference we wish to shed some light on which characteristics systematically differ across followers of individual brands. To do so, we ranked brands within different product categories based on their prevalence of specific facial characteristics among their followers, highlighting the top-ranking examples.

For illustration, in the automotive category, we found clear variation in facial appearance. Men Mercedes followers had the highest rate of baldness (16.4% vs. 15.1% as the category average), while Tesla followers, were more likely to wear reading glasses (19.7% vs. 15.2% as the category average) and have gray hair (6.3%, which is 28% higher than the category average). Among women, Tesla followers displayed high rates of eye makeup usage (85.4%) and expressed the highest levels of happiness (69.1%).

In the retail sector, Barnes & Noble followers stood out for their use of reading glasses (22.1% of men and 16.3% of women followers). In the apparel category, Diesel's men followers

had the highest rates of beards (26%) and sideburns (18.1%). Sephora's women followers showed the highest rates of eye makeup usage (89.3%).

These descriptive, model-free patterns, demonstrate systematic associations between facial appearance characteristics and brand preferences controlling for the gender of the follower. These systematic differences provide initial anecdotal evidence that facial characteristics may predict brand preferences.

### **STUDY 1: FACES CAN PREDICT BRAND PREFERENCES**

In study 1, our goal is to examine whether facial appearance can predict brand preferences among Twitter users. Focusing on within-category brand comparisons, such as followers of Miller Lite vs. Bud Light in the alcoholic beverages category, we tested whether brand followership can be accurately predicted based solely on users' facial appearance. Prediction accuracy above chance would suggest that facial appearance contains meaningful information that allows for successful and unobtrusive inference of brand preferences. To assess whether facial characteristics provide predictive information beyond basic demographic characteristics, though these demographics are most easily recovered through faces, we also compare our full model against a baseline model that uses the inferred age and gender.

#### **Method and Procedure**

To evaluate whether users' faces in our sample indicate brand preferences (as approximated via the brand followership), we created all possible brand pairs within each category from the 444 brands in our dataset<sup>6</sup> and used the Twitter users' facial characteristics to predict which of the two brands a user prefers. In total, we analyzed 3,426 brand pairs, including

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<sup>6</sup> We use as a brand category definition, the BAV brand categories. For an overview of the categories see appendix A.

all possible combinations of two brands within a category. To ensure a balanced sample of profile pictures across the brand pair comparisons and to make sure that a 50/50 chance is the appropriate benchmark, we drew a random sample of 500 user profile pictures per brand pair (i.e., 250 per brand). This setup allows for a meaningful baseline accuracy of 50%. If fewer than 250 profile pictures were available for one of the brands, we adjusted the sample size to match the smaller group within the pair.

We used a random forest classifier (Breiman 2001), a versatile machine learning method, to predict followership for each of the 3,426 brand pairs. In pairwise comparison, users followed only one brand, enabling a binary classification (0 = does not follow the brand, 1 = follows the brand). As input features, we used the 27 face characteristics extracted from each profile picture.

The prediction procedure was as follows: For each brand pair, we split the 500 images randomly into 80% training data and 20% test data. Within the 80% training set, we performed 5-fold cross-validation to tune the random forest's main hyperparameter, that is, the number of randomly selected features (5 or 27 per split; Breiman 2001). We repeated this 80/20 train-test split five times, each time randomly selecting users, and averaged the resulting accuracy scores to obtain out-of-sample performance estimates and compute standard errors. For further details on the training procedure, see web appendix A.

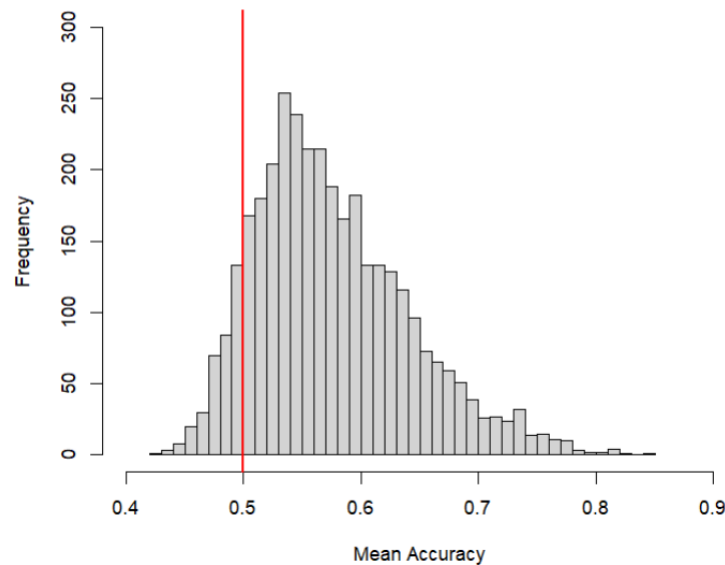
## **Results**

Across the 3,426 brand-pair comparisons, the trained model achieved a mean accuracy of 57.7% (SD = 0.066), significantly above the 50% chance baseline ( $t(3,425) = 67.828, p < .001$ ), with performance ranging from 42.4% (Clinique vs. Covergirl) to 84.6% (QVC vs. Golf Channel). Even for close competitors such as Apple vs. Microsoft (58.2%), Mercedes vs. Tesla

(67.4%), and Heineken vs. Budweiser (57%) predictive accuracies are significantly higher than the random-chance baseline. Figure 3 presents the distribution of out-of-sample classification accuracies across all 3,426 brand pairs.

**FIGURE 3**

**PAIRWISE CLASSIFICATION ACCURACIES ACROSS BRAND PAIRS**



*Note.* The histogram presents the distribution of the mean accuracies (i.e., correct predictions over all predictions) for each within-category brand pair. The red line indicates the 50% random-chance baseline. The distribution is significantly shifted to the right, indicating that brand followership can be successfully predicted from profile pictures.

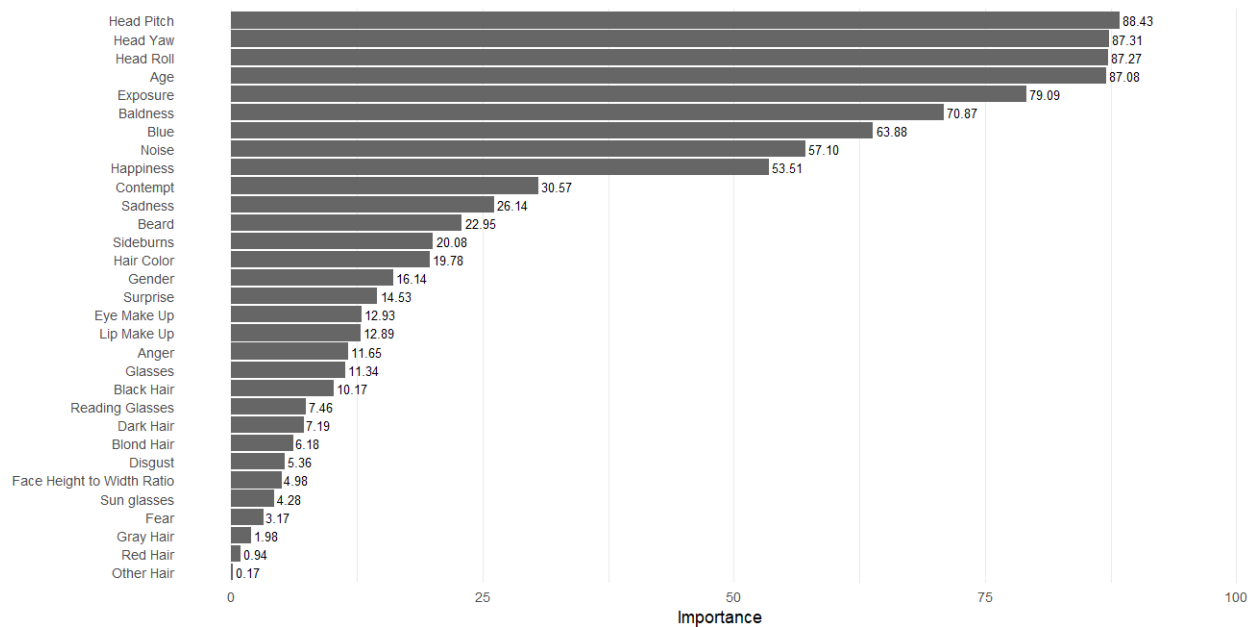
In addition to strong predictive performance, the random forest approach offers interpretable measures of variable importance, an advantage over “black box” deep neural networks trained on raw pixel data (Rai 2020; Witte et al. 2026). The analysis of feature importance revealed that head position cues (pitch, yaw, and roll) were among the most predictive features, as figure 4 shows. These subtle self-presentation choices—whether looking straight ahead, tilting the head, or turning to the side—were more informative than demographic

features, suggesting that how users compose their profile images reflects identity-relevant signals.

Notably, age ranked only fourth and gender only fifteenth in importance. Features with higher predictive value than age and gender, as head yaw and image quality indicators (e.g., exposure, blur), showed only weak to moderate correlations with demographic variables (see web appendix B), indicating that their predictive power stems from capturing distinct, non-demographic information.

**FIGURE 4**

**MEAN VARIABLE IMPORTANCE MEASURES OF RANDOM FOREST FROM BRAND PAIR PREDICTIONS**



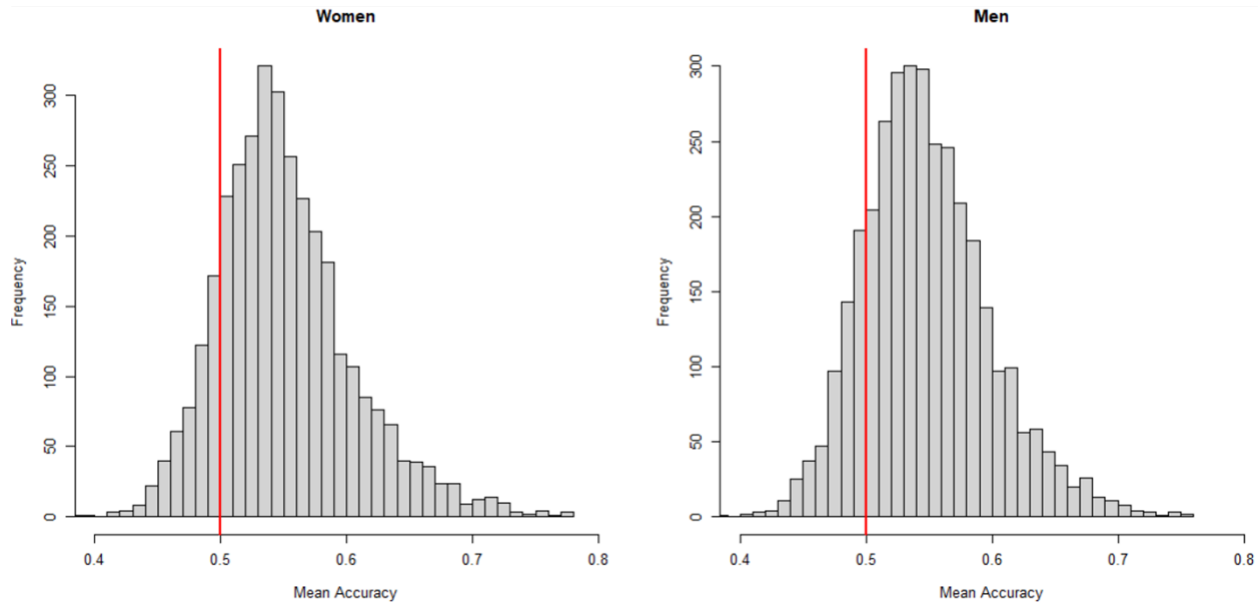
*Note.* For each experiment (i.e., each of the N=3,426 brand pairs), we extract the 27 variable importance measures. The variable importance measure ranges from 0 to 100, where 100 represents the highest importance of a facial feature. Afterwards, we compute the mean scores for each feature. Web appendix C presents the histograms for all variable importance measures, sorted by decreasing mean variable importance.

## **Robustness Check: Brand-Face Match Beyond Demographics**

We conduct additional analyses to isolate the contribution of facial characteristics beyond estimated age and inferred gender. First, we train a random forest model only on the two demographic features as a baseline model and compare it to our full model, incl. all 27 facial characteristics. The full model outperformed a baseline model that used only age and gender as predictors by 2.3% points (mean accuracy full model = 57.7% vs. mean accuracy demographics model = 55.4%;  $t(6,778.9) = 14.979, p < .001$ ), demonstrating that facial characteristics provide additional predictive power beyond basic demographics. Second, we reran the classification analysis separately for men and women (Kachur et al. 2020). The results remained robust: the model achieved mean accuracies of 55.18% (SD = 0.054) for women and 54.87% (SD = 0.050) for men, both significantly above the 50% baseline ( $t(3,425) = 56.571, p < .001$  for women;  $t(3,425) = 56.938, p < .001$  for men). Figure 5 presents the distribution of classification accuracies for all 3,426 brand pairs, split by inferred gender. Table 2 presents the average accuracy across all categories as well as the most accurately predicted brand per category, separately for men and women.

### **FIGURE 5**

DISTRIBUTION OF PAIRWISE CLASSIFICATION ACCURACIES FOR ALL WITHIN-CATEGORY BRAND PAIRS (SPLIT BY INFERRED GENDER)



*Note.* N=3,426 brand pairs per gender (i.e., all possible within-category combinations). The red line indicates the random chance level.

**TABLE 2**

**AVERAGE ACCURACY ACROSS CATEGORIES AND TOP BRANDS:  
SPLIT BY INFERRED GENDER**

<b>BAV category (sorted alphabetically)</b>	<b>Brand with highest average accuracy</b>	<b>Brand accuracy (within category)</b>	<b>Category accuracy</b>
<i>Panel A: Women</i>			
Airlines	Star Alliance	0.551	0.533
Assorted Financial Services	MoneyGram	0.637	0.565
Automobiles	Tesla	0.562	0.538
Banks	Chase	0.538	0.525
Basketball Events & Organizations	Miami Heat	0.555	0.546
Beauty Products for the Face, Skin & Nails	Burt's Bees	0.626	0.553
Beers	Miller Lite	0.542	0.521
Carbonated Soft Drinks	Coca Cola	0.562	0.551

<b>BAV category (sorted alphabetically)</b>	<b>Brand with highest average accuracy</b>	<b>Brand accuracy (within category)</b>	<b>Category accuracy</b>
Charity & Non-Profit Organizations	American Heart Association	0.571	0.539
Clothing & Footwear Retailers	PacSun	0.631	0.585
Computers & Computer Related Products	Microsoft	0.580	0.557
Consulting Firms	EY News	0.589	0.566
Consumer Electronics such as Stereos, TVs & VCRs	Sony	0.593	0.562
Department Stores & Mass Merchandisers	HomeGoods	0.568	0.543
Extreme Sports Clothing & Equipment	Burton	0.583	0.568
Fashion Designers	kate spade	0.599	0.546
Fast Food & Restaurant Chains	Chipotle	0.573	0.540
Film Studios & Entertainment Companies	Disney	0.543	0.533
Football Events & Organizations	Raiders	0.529	0.512
Gasoline/Petroleum	Chevron	0.540	0.514
Hotels & Motels	InterContinental	0.555	0.526
Industrial Corporations	Siemens	0.589	0.538
Internet Commerce Retail	Staples	0.568	0.546
Internet Commerce Service	Ebay	0.588	0.533
Internet Communication	Viber	0.545	0.525
Internet Finance	Mint	0.498	0.498
Internet News/Information	Fox TV	0.575	0.537
Internet Search	Google	0.515	0.503
Internet Tools and Services	Firefox	0.595	0.567
Magazines & Newspapers (Business & Personal Finance)	Money	0.525	0.510
Magazines & Newspapers (General Interest)	Ebony Magazine	0.714	0.595
Magazines & Newspapers (Newsweeklies)	Newsweek	0.564	0.549
Pharmaceutical Companies	Merck	0.527	0.511
Specialty Retail Stores	Sephora	0.595	0.561

<b>BAV category (sorted alphabetically)</b>	<b>Brand with highest average accuracy</b>	<b>Brand accuracy (within category)</b>	<b>Category accuracy</b>
Spirits & Liquors	Maker's Mark	0.572	0.543
Sport & Leisure Shoes	New Balance	0.617	0.553
Sporting Equipment	Ping	0.500	0.500
Sports & Casual Clothing	Under Armour	0.603	0.561
Supermarkets, Hypermarkets & Convenience Stores	7-Eleven	0.549	0.538
Telecommunications Companies	Boost Mobile	0.558	0.528
Television Stations	Nickelodeon	0.706	0.569

*Panel B: Men*

Airlines	Singapore Airlines	0.604	0.553
Assorted Financial Services	MoneyGram	0.633	0.555
Automobiles	Tesla	0.604	0.537
Banks	HSBC	0.564	0.536
Basketball Events & Organizations	LA Lakers	0.571	0.554
Beauty Products for the Face Skin & Nails	Burt's Bees	0.641	0.547
Beers	Heineken	0.558	0.532
Carbonated Soft Drinks	Mountain Dew	0.574	0.549
Charity & Non-Profit Organizations	American Heart Association	0.565	0.531
Clothing & Footwear Retailers	PacSun	0.636	0.581
Computers & Computer Related Products	Microsoft	0.569	0.549
Consulting Firms	EY News	0.588	0.562
Consumer Electronics such as Stereos, TVs & VCRs	Sony	0.584	0.556
Department Stores & Mass Merchandisers	HomeGoods	0.558	0.536
Extreme Sports Clothing & Equipment	Burton	0.594	0.575
Fashion Designers	kate spade	0.616	0.551
Fast Food & Restaurant Chains	Chipotle	0.574	0.543
Film Studios & Entertainment Companies	Pixar	0.555	0.534

<b>BAV category (sorted alphabetically)</b>	<b>Brand with highest average accuracy</b>	<b>Brand accuracy (within category)</b>	<b>Category accuracy</b>
Football Events & Organizations	Raiders	0.537	0.519
Gasoline/Petroleum	Chevron	0.543	0.514
Hotels & Motels	InterContinental	0.554	0.523
Industrial Corporations	Siemens	0.584	0.540
Internet Commerce Retail	Staples	0.569	0.548
Internet Commerce Service	Ebay	0.579	0.531
Internet Communication	Viber	0.551	0.524
Internet Finance	Mint	0.505	0.497
Internet News/Information	Fox TV	0.584	0.541
Internet Search	Google	0.521	0.506
Internet Tools and Services	Firefox	0.600	0.565
Magazines & Newspapers (Business & Personal Finance)	Money	0.527	0.511
Magazines & Newspapers (General Interest)	Ebony Magazine	0.700	0.591
Magazines & Newspapers (Newsweeklies)	Newsweek	0.567	0.549
Pharmaceutical Companies	Merck	0.529	0.510
Specialty Retail Stores	Sephora	0.591	0.559
Spirits & Liquors	Maker's Mark	0.577	0.546
Sport & Leisure Shoes	New Balance	0.613	0.551
Sporting Equipment	Ping	0.504	0.501
Sports & Casual Clothing	Under Armour	0.605	0.562
Supermarkets, Hypermarkets & Convenience Stores	7-Eleven	0.553	0.539
Telecommunications Companies	Boost Mobile	0.560	0.530
Television Stations	Nickelodeon	0.685	0.565

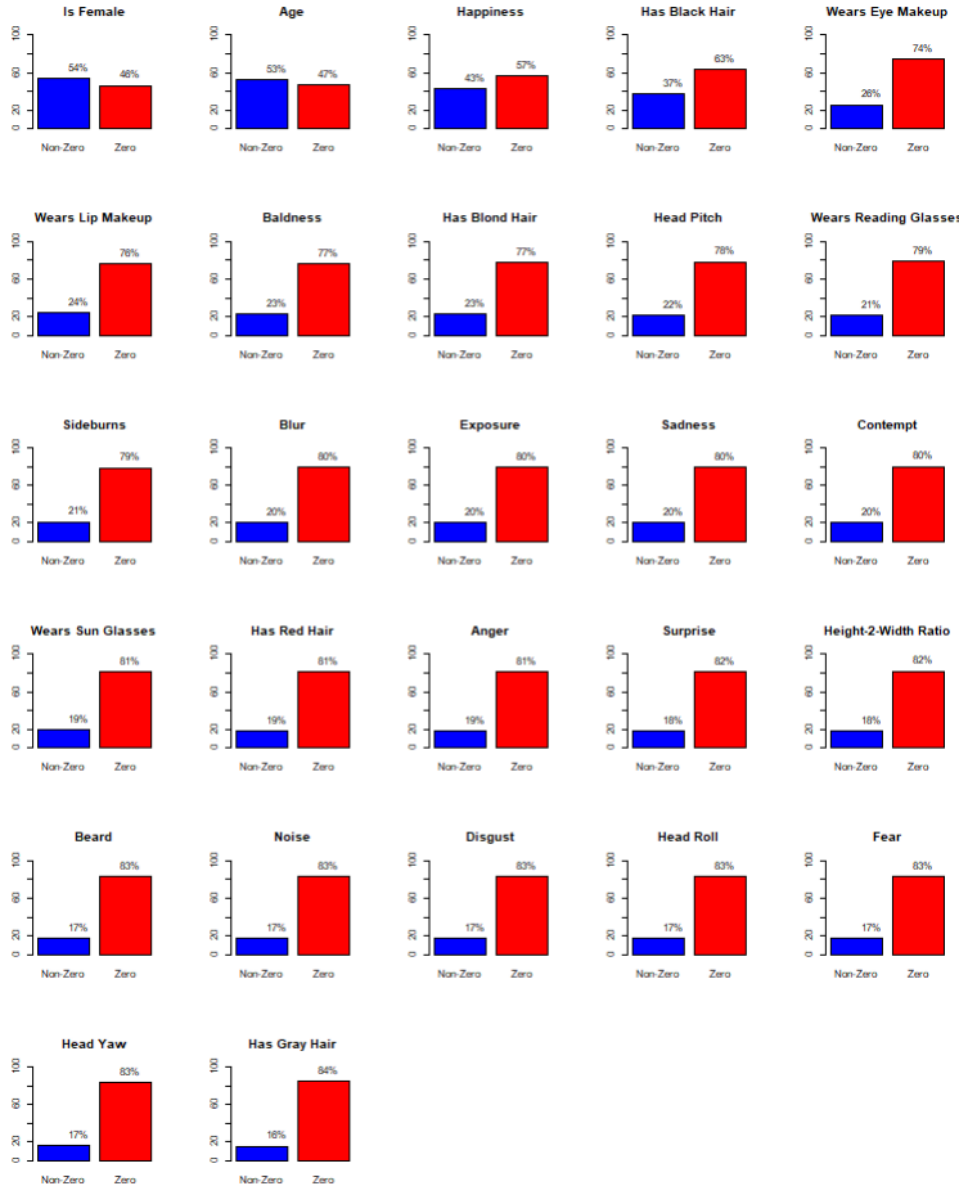
*Note.* Accuracy reflects the random forest classifier's ability to correctly identify brand followers based on facial appearance. BAV = Brand Asset Valuator.

Third, we estimate a binary LASSO (Least Absolute Shrinkage and Selection Operator) regression using the identical data and features as the random forest analysis, that is, the same set of 3,426 brand pairs and brand choice (brand A vs. brand B) as the dependent variable of each brand pair. The LASSO regression has the appealing property that it performs automated feature selection, setting all coefficients to zero, which are not informative for solving the brand pair prediction task. If the demographics age and gender were the only two relevant features, we would expect them to be the only two variables to have non-zero coefficients in the LASSO regressions and, in turn, expect zero coefficients for the remaining 25 facial characteristics. Figure 6 presents the aggregated results of the 3,426 LASSO regressions that we estimate based on the brand pairs. The variables in the figure are sorted by the highest non-zero coefficients share (rank 1) to lowest (rank 27). Consistent with our random forest results, and supporting the robustness of our earlier findings, the high share of non-zero coefficients among variables beyond age and gender confirms our previous results that the empirical brand-face match that we identify extends beyond mere demographics. Figure 6 indicates, for example, that face expressions (happiness, rank 3), transient features (hair color, rank 4, as well as eye and lip make-up, ranks 5 and 6), and accessories (reading glasses, rank 10) are informative for brand preferences of consumers. Consistent with expectations, the importance of facial characteristics also varies by product categories. For example, for cosmetics brands, the share of zero coefficients for eye and lip makeup reduces from 74% and 76% to 67% and 68%, respectively, highlighting stronger predictive value for these features in classifying brand pairs.

Taken together, these findings support our core premise: consumers' curated social media profile faces convey rich information that enable accurate and unobtrusive prediction of brand preferences, beyond what can be inferred from age or gender alone.

FIGURE 6

LASSO COEFFICIENTS FROM BRAND PAIR PREDICTIONS



Note. Blue bars indicate non-zero coefficients from LASSO regression. Red bars indicate zero coefficients. The 27 panels are sorted from highest non-zero coefficients share (gender) to lowest (gray hair). Web appendix D presents the histograms of the LASSO coefficients.

## **STUDY 2: COMPETING BRANDS WITH SIMILAR IDENTITIES SHOW LOWER FACE-BRAND ACCURACIES**

In study 1, we demonstrated that facial characteristics can predict which brand a Twitter user follows with accuracy significantly above chance. However, prediction accuracies varied across brand pairs (figure 3). Some comparisons, such as Apple vs. Microsoft, yielded accuracies around 60% (58.2%), while others, like Mercedes vs. Tesla, approach 70% (67.4%), with accuracies ranging from 42.4% to 84.6%. This variation suggests that some brands attract followers with more visually distinct faces, whereas others share a more visually homogenous follower base.

In study 2, we examine whether this variation can be explained by brand identity similarity, measured by brand personality dimension from the Brand Asset Valuator (BAV). For example, Microsoft and Apple, whose classification accuracy was relatively modest, show high similarity in brand personality (standardized similarity = 0.92). In contrast, Mercedes and Tesla, whose followers were more easily distinguishable, show much lower personality similarity (standardized similarity = 0.18).

We hypothesize that the more similar two competing brands in personality, the more similar their followers will appear, leading to lower face-based classification accuracy. To test this, we examined whether the prediction accuracy from study 1 for each brand pair was systematically associated with the similarity of their brand personalities. Specifically, we ask: do brands with overlapping identities (measured by their personality characteristics) attract users with more similar faces?

### **Method and Procedure**

To address this question, we used the classification accuracies obtained from Study 1, where we ran separate models for women and men users across all brand pairs. A high accuracy of a brand pair prediction indicates that the faces of the two brands are distinct from each other, hence easier to distinguish by the machine learning classifier, while a low accuracy relates to a higher similarity of the faces of the brand followers. We define prediction accuracy as the hit rate (correct predictions divided by total predictions), the most commonly used evaluation measure for image classification tasks in marketing (Witte et al. 2026). This yielded two accuracy scores per brand pair (one for women and one for men), which we used as dependent variables in our regression analysis.<sup>7</sup>

To do so, we augment our Twitter dataset using an external source of brand perceptions from the marketing agency Young & Rubicam (Y&R). Y&R conducts a quarterly survey of brand perceptions across a large U.S. consumer panel (Y&R Brand Asset Valuator (BAV))<sup>8</sup>. Brands are rated on a host of human personality characteristics such as “authentic,” “leader,” and “intelligent” (Aaker 1997), which gives us a comprehensive list of brand personality characteristics. It has been established that BAV is a reliable measure to assess consumers’ brand perceptions, e.g., the degree to which a brand is perceived as intelligent, glamorous, fun, down-to-earth, arrogant, or rugged (Mizik and Jacobson 2008; Stahl et al. 2012). Its relevance is further confirmed by the large body of research that has used BAV brand perception to show how various marketing actions are related to and can impact brand equity (Datta, Ailawadi, and Van Heerde 2017; Klein et al. 2019; Qorbani, Koosha, and Bagheri 2021).

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<sup>7</sup> Model 1 pools both genders (6,852 observations: 3,426 brand pairs \* 2 genders), while Models 2 and 3 present results separately for women and men users, respectively.

<sup>8</sup>See <https://www.bavgroup.com/about-bav/brandasset-valuatorr> for additional information.

For all 444 brands in our data, we have access to the brand personality characteristics across 47 dimensions rated by a representative panel of U.S. consumers (see web appendix E for the complete list and summary statistics). Each brand thus has a 47-dimensional vector that reflects the consumers' perception on the 47 brand dimensions. We use these vectors of all brand pairs to assess how similar the two brands are in terms of their brand personality. Specifically, we compute the cosine similarity between both brands' personality vectors. We expect that similarity is negatively associated with classification accuracy, as an increasing brand similarity can be expected to translate to a higher user similarity (higher similarity of consumer faces) and thus lower prediction accuracy.

To assess whether the brand identity, reflected by the 47 BAV personality characteristics, is related to the ability to accurately predict brand preferences based on consumers' facial appearance, we estimated a linear regression model with the logit transformed classification accuracy as the dependent variable to cover the real space, the cosine similarity between BAV measures of the two brands as the focal predictors, and a set of explanatory variables, that serve as controls. Our control variables include the overlap between the followers across both brands, and the size of the training data used for the pairwise prediction. Recall that not for each brand pair we have access to 500 faces as training data. This creates a natural variation in training data that we can exploit to explain how a larger sample size is related to classification accuracy. Following our approach in study 1 where we split brand pairs by gender (Kachur et al. 2020), we can control for gender in our regression and test whether brand pair prediction is systematically easier for men versus women consumers.

## **Results**

As expected, Model (1) in table 3 confirms that greater brand personality similarity within brand pairs is associated with significantly lower classification accuracies ( $\beta_{\text{bav}} = -0.0259, p < .001$ ). In other words, the more two competing brands share similar personality characteristics, the harder it becomes to distinguish their followers based on facial appearance. Conversely, when brands have more distinct personalities, facial appearance more reliably predicts brand followership.

Importantly, the effect of brand personality similarity remains significant even when accounting for alternative explanations, including follower overlap between the two brands, sample size of the training data, and inferred gender of users. As expected, we find that a greater follower overlap is related to a decrease in classification accuracy, while increases in the size of the training data are positively associated with prediction accuracy.

**TABLE 3**  
EXPLAINING VARIATION IN CLASSIFICATION ACCURACY BETWEEN BRAND  
PAIRS

	<b>Model 1: Women &amp; men</b>	<b>Model 2: Women only</b>	<b>Model 3: Men only</b>
BAV Similarity	-.0259*** (.0069)	-.0318*** (.0080)	-.0193** (.0069)
User Overlap	-.3874*** (.0490)	-.3932*** (.0631)	-.4128*** (.0584)
Sample Size (in 100)	.0258*** (.0048)	.0306*** (.0075)	.0226*** (.0067)
Gender: Men	-.0035 (.0062)	—	—
Fixed Effects: BAV Category	Yes	Yes	Yes
S.E.: Clustered by	Brand 1 & Brand 2	Brand 1 & Brand 2	Brand 1 & Brand 2
Observations	6,852	3,426	3,426
R <sup>2</sup>	.15249	.16719	.15479
Within R <sup>2</sup>	.05966	.06197	.05977

*Note.* Models 2 and 3 are split by women and men users, respectively. Standard errors in parentheses.  $p < .01$  \*\*,  $p < .001$  \*\*\*.

Taken together, study 2 demonstrates that the relationship between consumer faces and their brand preferences is related to brand personality: users with distinct facial characteristics are more easily matched to brands with distinct personalities. Next, as consumer faces aggregate multiple dimensions of information, such as demographics, head position, emotional expressions, accessories, face shape, and image-level quality, study 3 investigates which of these specific characteristics are most closely associated with preferences for particular brand personality traits.

### **STUDY 3: MERCEDES LOVERS ARE BALD, WHILE TESLA FOLLOWERS HAVE GRAY HAIR: FACES REFLECT BRAND IDENTITY**

In study 2, we found that brands with similar identities are followed by Twitter users who share similar facial appearance characteristics. Building on this finding, study 3 examines whether a brand's identity is congruent with the consumer identity inferred from followers' facial characteristics. To do so, we analyzed the full set of brands each user follows, mapped the personality dimensions of those brands, and examined how these dimensions relate to the user's facial characteristics.

#### **Method and Procedure**

Each brand in our data is associated with 47 brand personality dimensions. Each user follows an average of 19 brands out of the 444 brands in our dataset ( $SD = 23$ ,  $Median = 11$ ). For each user, we construct a user-level brand-personality vector by aggregating BAV measures across the brands they follow.

To reflect the importance of each brand in a user's unique brand portfolio, we adapt the term frequency-inverse document frequency (tf-idf) weighting scheme from the text retrieval

literature. The purpose of this weighting scheme is to assign higher weights to brands that fewer users follow, making them more distinctive and consequently more influential in the overall average score. The intuition is that it is less informative if users follow commonplace brands like Google, Budweiser, or Nike compared to niche brands with only few followers like Lucky Brand, Roxy, or Dogfish Head Brewery. Hence, given a user,  $u$ , and a brand,  $b$ , we employ what we call “brand frequency-inverse user frequency” (bf-iuf) weighting as follows:

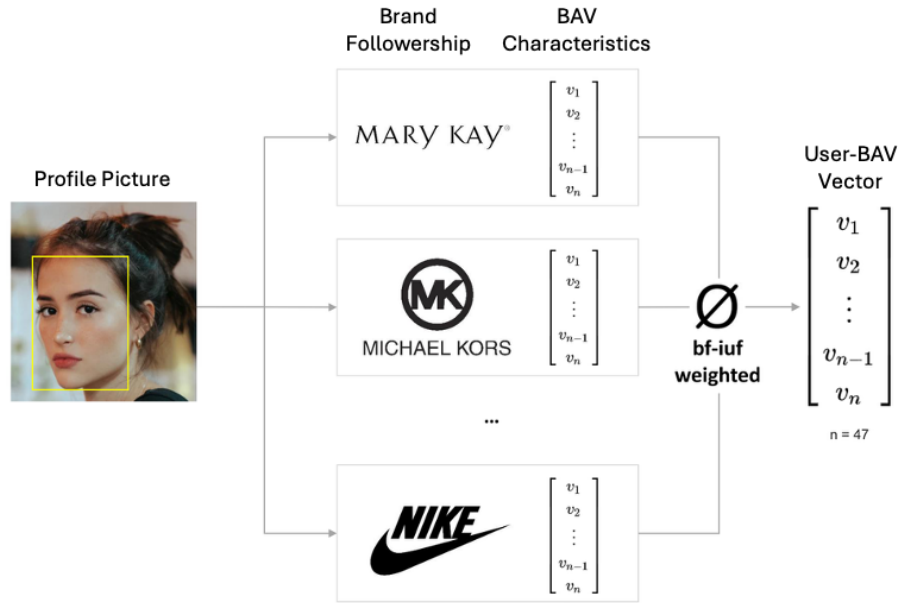
$$bf \cdot iuf(b, u) = bf(b, u) * iuf(u),$$

where  $bf(b, u) = \frac{1}{|B_u|}$  represents the brand frequency—the inverse of the number of brands user  $u$  follows (where  $|B_u|$  denotes the brand count for user  $u$ )—and  $iuf(u) = \ln\left(\frac{N}{n_b}\right)$  represents the inverse user frequency, where  $N$  is the total number of users in our dataset and  $n_b$  is the number of users following brand  $b$ . This approach assigns lower weights to commonly followed brands, while niche brands followed by selective users receive higher weights.

Assigning these bf-iuf weighted BAV dimensions to individual users is an intuitive matrix multiplication of the brands the user follows ( $U_{Brands}$ ), the brand-weighting matrix ( $W_{bf.iuf}$ ) from the equation above, and the brand-BAV characteristics ( $B_{BAV}$ ), yielding a user-BAV matrix ( $U_{BAV}$ ) with 122,161 user rows and 47 columns representing the BAV dimensions. Figure 7 provides a high-level illustration of this procedure to obtain user-level brand preference vectors.

## FIGURE 7

### AGGREGATING TWITTER USERS’ BRAND FOLLOWERSHIP TO BRAND PREFERENCE VECTORS



After we have assigned a weighted average brand preference vector to each user, we explore the association between the user’s facial characteristics and brand dimensions. Given that many of the BAV brand personality dimensions share common features such as “arrogant” and “unapproachable” or “dynamic” and “energetic” we aggregate the features into five components reflecting different types of brand personalities using a principal component analysis (PCA). PCA allows us to reduce dimensionality of the data while preserving maximum variance in the data. We identify five principal components that reflect different types of brand personalities and explain approximately 80% of the total variance.<sup>9</sup> Below we list the five personality types identified via the principal component analysis and display the single brand personality traits with the highest correlation (in parentheses) to each principal component (see web appendix F for all BAV dimensions’ correlations):

1. *The distant brand*: arrogant (.45), intelligent (.30), unapproachable (.28), up-to-date (.21)

<sup>9</sup> Note subsequent components only contribute minimally to variance reduction (less than 3% each; see web appendix G for a scree plot of eigenvalues).

2. *The glamorous brand*: glamorous (.86), upper-class (.83), stylish (.82), prestigious (.79)
3. *The smart brand*: intelligent (.64), reliable (.49), trustworthy (.48), high-performance (.47)
4. *The adventurous brand*: rugged (.62), energetic (.59), daring (.40), dynamic (.33)
5. *The edgy brand*: innovative (.78), progressive (.65), different (.62), dynamic (.62)

Next, we regressed the 5 brand personality types from the PCA (distant, glamorous, smart, adventurous, and edgy brands) on the set of 27 facial characteristics of a user. To rule out alternative explanations related to the network size, status, and activity of Twitter users, we controlled in our analysis for the number of followers, friends, likes, statuses, and brands followed by the users.

## Results

To test the associations observed in the descriptive analysis, we conducted a regression analysis linking specific facial appearance characteristics to broader brand personality traits across the full dataset. This analysis builds on the findings of study 2 by offering a more fine-grained understanding of how particular facial characteristics align with distinct brand personality traits. The regression results are presented in table 4, with gender-specific findings reported in table 5, consistent with previous studies.

Below we highlight some of the most interesting relationships between facial characteristics and brand personality types. Across personality dimensions, the findings reveal several congruent patterns between the brand identity characteristics and consumers' facial features:

Reading Glasses: Followers of "smart" brands like Microsoft and Barnes & Noble were more likely to wear reading glasses ( $\beta=0.063$ ,  $p < .001$ ). But while this association was strong and

positive for men ( $\beta_{\text{men}}=0.177, p < .001$ ), it was surprisingly negative for women ( $\beta_{\text{woman}}=-0.10, p < .001$ ).

**Makeup:** Glamorous brands like Sephora attract followers with higher rates of eye and lip makeup ( $\beta_{\text{eye}}=0.282, p < .001$ ;  $\beta_{\text{lip}}=0.245, p < .001$ ). In contrast, "smart" and "adventurous" brands like Intel and The North Face see less makeup among their followers.

**Beards and Sideburns:** "Edgy" brands like Timberland draw followers with more facial hair—beards ( $\beta=0.185, p < .001$ ) and sideburns ( $\beta=0.119, p < .05$ ).

**Baldness:** Mercedes followers stand out for their higher baldness rates among men (16.4%), while Tesla followers have more gray hair (6.3%).

**Happiness and Angriiness:** Followers of "adventurous" brands like Diesel tend to look happier ( $\beta=0.059, p < .001$ ) but also angrier ( $\beta=0.332, p < .001$ ). Meanwhile, "glamorous" brand followers, such as Chanel and Louis Vuitton, show less emotion overall, with lower levels of happiness ( $\beta=-0.357, p < .001$ ), angriiness ( $\beta=-0.320, p < .05$ ), and sadness ( $\beta=-0.303, p < .01$ ).

**Sunglasses:** "Edgy" brands like Tesla, "smart" brands like Google, and "glamorous" brands like Versace are linked to users who wear sunglasses ( $\beta=0.043, p < .05$ ;  $\beta=0.108, p < .001$ ;  $\beta=0.132, p < .001$ ), suggesting a polished and stylish self-presentation.

**Disgust:** "Distant" brands such as Goldman Sachs stand out for attracting followers with higher expressions of disgust ( $\beta=2.627, p < .01$ ), setting them apart from other personality types.

These findings highlight how specific facial characteristics align with brand personalities in ways that resonate with societal stereotypes and consumer expectations. For example, reading glasses as a "marker" of intelligence or makeup as an indicator of glamour seem to align neatly

with brand personalities, providing evidence that consumer identities reflected in their faces seem to be congruent with brand identities and thus brand preferences.<sup>10</sup>

**TABLE 4**  
REGRESSION RESULTS: PREDICTING BAV DIMENSIONS FROM FACIAL  
CHARACTERISTICS (OLS)

	<i>Dependent variable:</i>				
	<b>Smart</b>	<b>Adventurous</b>	<b>Glamorous</b>	<b>Edgy</b>	<b>Distant</b>
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>	<b>(5)</b>
Age (in 10 Yrs)	.252*** (.006)	.027*** (.005)	-.151*** (.008)	-.121*** (.005)	-.009 (.016)
Is Women	-.741*** (.017)	-.556*** (.015)	.220*** (.023)	-.295*** (.014)	-.431*** (.047)
Wears Reading Glasses	.063*** (.016)	-.057*** (.014)	-.222*** (.021)	.114*** (.013)	-.027 (.044)
Wears Sunglasses	.108*** (.021)	.028 (.018)	.132*** (.028)	.043* (.018)	-.116* (.058)
Wears Eye Makeup	-.132*** (.014)	-.077*** (.012)	.282*** (.019)	.098*** (.012)	.127*** (.039)
Wears Lip Makeup	-.044*** (.013)	.058*** (.012)	.245*** (.018)	.008 (.011)	.068* (.037)
Beard	.076 (.046)	.008 (.041)	-.196** (.062)	.185*** (.039)	-.175 (.128)
Sideburns	.041 (.060)	.227*** (.054)	.171* (.082)	.119* (.051)	-.127 (.168)
Baldness	-.200*** (.034)	.130*** (.031)	.018 (.047)	-.383*** (.029)	.050 (.096)
Has Blond Hair	-.055** (.018)	.020 (.016)	.010 (.024)	-.081*** (.015)	-.251*** (.049)
Has Black Hair	.107*** (.011)	-.061*** (.010)	.099*** (.015)	.057*** (.010)	.480*** (.032)
Has Gray Hair	-.206*** (.030)	-.001 (.027)	.235*** (.041)	.028 (.026)	.372*** (.084)
Has Red Hair	-.039 (.042)	.004 (.038)	-.113* (.058)	.034 (.036)	.277* (.118)
Head Pitch (in 100)	-.050 (.059)	.257*** (.052)	-.793*** (.080)	-.326*** (.050)	-.405* (.164)
Head Roll (in 100)	-.064 (.056)	-.104* (.049)	-.175* (.076)	.017 (.047)	-.047 (.155)
Head Yaw (in 100)	-.008 (.036)	.035 (.032)	-.148** (.049)	.016 (.030)	-.065 (.100)

<sup>10</sup> In web appendix H, we also report the regressions on each of the single BAV variables.

	<i>Dependent variable:</i>				
	<b>Smart (1)</b>	<b>Adventurous (2)</b>	<b>Glamorous (3)</b>	<b>Edgy (4)</b>	<b>Distant (5)</b>
Exposure	.311*** (.031)	-.142*** (.028)	.082 (.042)	.074** (.026)	-.070 (.087)
Blur	-.133*** (.021)	.043* (.019)	-.090** (.029)	-.068*** (.018)	-.179** (.059)
Noise	-.070*** (.020)	-.020 (.018)	.031 (.027)	-.021 (.017)	-.066 (.056)
Height-to-Width Ratio	-.643* (.269)	-.282 (.239)	1.116** (.366)	.231 (.228)	-.112 (.750)
Happiness	.131*** (.012)	.059*** (.011)	-.357*** (.016)	-.074*** (.011)	-.222*** (.034)
Anger	-.474*** (.010)	.332*** (.090)	-.320* (.137)	.105 (.085)	-1.255*** (.281)
Contempt	-.820*** (.095)	.138 (.085)	-.409*** (.130)	.078 (.081)	-1.380*** (.266)
Disgust	-.696* (.303)	.364 (.269)	-1.004* (.412)	-.045 (.256)	2.690** (.844)
Fear	-.282 (.346)	.485 (.307)	.026 (.470)	.296 (.293)	.647 (.964)
Sadness	-.531*** (.094)	.331*** (.084)	-.303* (.128)	.090 (.080)	-.464 (.262)
Surprise	-.367*** (.071)	.180** (.063)	-.251** (.097)	-.068 (.060)	-.548** (.198)
Number of Followers (ln)	.135*** (.006)	-.072*** (.005)	-.012 (.008)	-.065*** (.005)	-.090*** (.016)
Number of Friends (ln)	-.083*** (.008)	-.159*** (.007)	-.174*** (.011)	.082*** (.007)	-.381*** (.022)
Number of Likes (ln)	-.009*** (.002)	-.065*** (.002)	-.038*** (.003)	-.016*** (.002)	-.039*** (.007)
Number of Statuses (ln)	-.103*** (.003)	-.039*** (.003)	-.039*** (.005)	-.038*** (.003)	-.133*** (.009)
Brand Count (ln)	.169*** (.006)	-.384*** (.006)	-.328*** (.009)	-.126*** (.005)	.156*** (.018)
Observations	122,161	122,161	122,161	122,161	122,161
R <sup>2</sup>	.111	.096	.050	.029	.019
F Statistic	478.408***	405.988***	200.625***	112.671***	72.535***

*Note.* Standard errors in parentheses.  $p < .05$  \*,  $p < .01$  \*\*,  $p < .001$  \*\*\*.

**TABLE 5**

REGRESSION RESULTS: PREDICTING BAV DIMENSIONS FROM FACIAL  
CHARACTERISTICS, BY GENDER (OLS)

	<i>Dependent variable:</i>				
	<b>Adventurous (1)</b>	<b>Glamorous (2)</b>	<b>Smart (3)</b>	<b>Edgy (4)</b>	<b>Distant (5)</b>
<i>Panel A: Women</i>					
Age (in 10 Yrs)	.043*** (.007)	-.228*** (.013)	.236*** (.008)	-.116*** (.007)	-.089*** (.024)
Wears Reading Glasses	.021 (.022)	-.317*** (.039)	-.100*** (.024)	.062** (.020)	-.281*** (.072)
Wears Sunglasses	.099** (.031)	.059 (.054)	.065 (.034)	-.006 (.028)	.008 (.102)
Wears Eye Makeup	-.100*** (.019)	-.460*** (.033)	-.092*** (.021)	.090*** (.017)	.176** (.062)
Wears Lip Makeup	-.094*** (.015)	.369*** (.027)	-.062*** (.017)	.020 (.014)	.155** (.050)
Has Blond Hair	.033 (.017)	.065* (.030)	-.048* (.019)	-.059*** (.016)	-.226*** (.057)
Has Black Hair	.014 (.014)	.153*** (.025)	.049** (.016)	.034** (.013)	.402*** (.047)
Has Gray Hair	.144* (.070)	.050 (.121)	-.093 (.076)	.149* (.063)	.763*** (.226)
Has Red Hair	.001 (.039)	-.145* (.068)	-.040 (.043)	.045 (.036)	-.321* (.128)
Head Pitch (in 100)	-.144 (.076)	-.850*** (.132)	.324*** (.083)	-.148* (.069)	-.012 (.248)
Head Roll (in 100)	.058 (.061)	.241* (.105)	-.020 (.066)	.005 (.055)	-.005 (.197)
Head Yaw (in 100)	.064 (.042)	.169* (.073)	-.080 (.046)	-.003 (.038)	-.155 (.137)
Exposure	-.085* (.039)	.081 (.067)	.125** (.042)	.006 (.035)	-.357** (.126)
Blur	.023 (.027)	-.100* (.047)	-.114*** (.029)	-.029 (.025)	.010 (.088)
Noise	-.066 (.026)	-.050 (.044)	.011 (.028)	.015 (.023)	.018 (.083)
Height-to-Width Ratio	.172 (.280)	.861 (.484)	-.316 (.306)	.171 (.254)	.378 (.909)
Happiness	.030 (.016)	-.584*** (.027)	.193*** (.017)	-.096*** (.014)	-.136* (.051)
Anger	.009 (.185)	-.979** (.230)	.304 (.202)	.085 (.168)	-1.291* (.600)
Contempt	.043 (.123)	-.603** (.213)	-.645*** (.135)	.032 (.112)	-1.162*** (.401)
Disgust	.076 (.409)	-.659 (.708)	-.685 (.446)	.083 (.372)	2.709* (1.329)
Fear	.910* (.123)	.244 (.123)	-.519 (.123)	.528 (.123)	1.322 (.123)

<i>Dependent variable:</i>					
	<b>Adventurous (1)</b>	<b>Glamorous (2)</b>	<b>Smart (3)</b>	<b>Edgy (4)</b>	<b>Distant (5)</b>
Sadness	(.439) .228*	(.759) -.841***	(.479) .251	(.399) .184	(1.425) .052
Surprise	(.124) .189*	(.215) -.414**	(.135) .125	(.113) .057	(.403) .097
Number of Followers (ln)	(.089) -.068***	(.153) -.011	(.097) .167***	(.081) -.072***	(.288) -.131***
Number of Friends (ln)	(.007) .280***	(.012) -.268***	(.008) .027*	(.007) .137***	(.023) .506***
Number of Likes (ln)	(.010) .046***	(.017) .009	(.011) -.012***	(.009) -.025***	(.032) .019
Number of Statuses (ln)	(.003) -.050***	(.005) .009	(.003) -.114***	(.003) -.029***	(.010) -.213***
Brand Count (ln)	(.004) -.455***	(.007) .438***	(.005) .107***	(.004) -.154***	(.014) .064*
Observations	(.008) 59,362	(.014) 59,362	(.009) 59,362	(.007) 59,362	(.026) 59,362
R <sup>2</sup>	.060	.257	.056	.021	.018
F Statistic	134.944***	127.444***	125.736***	46.393***	39.329***

*Panel B: Men*

Age (in 10 Yrs)	.029*** (.007)	.275*** (.008)	-.108*** (.010)	-.129*** (.007)	.040 (.022)
Wears Reading Glasses	-.080*** (.018)	.177*** (.021)	-.118*** (.024)	.117*** (.018)	.093 (.055)
Wears Sunglasses	-.030 (.023)	.090*** (.027)	.272*** (.031)	.076*** (.023)	-.146* (.070)
Beard	.018 (.042)	.027 (.049)	-.207*** (.056)	.190*** (.042)	-.255* (.129)
Sideburns	.203*** (.055)	.043 (.063)	.145* (.073)	.117* (.055)	-.084 (.168)
Baldness	.135*** (.039)	-.157*** (.045)	-.061 (.052)	-.452*** (.038)	.283* (.118)
Has Blond Hair	.025 (.035)	-.168*** (.040)	-.026 (.046)	-.201*** (.034)	-.286* (.106)
Has Black Hair	-.124*** (.014)	.134*** (.016)	.081*** (.019)	.059*** (.014)	.537*** (.043)
Has Gray Hair	-.031 (.031)	-.218*** (.036)	.115** (.041)	.012 (.031)	.188* (.094)
Has Red Hair	.082 (.108)	-.158 (.125)	.121 (.145)	-.039 (.108)	-.111 (.331)
Head Pitch (in 100)	.572*** (.071)	-.275*** (.082)	-.719*** (.095)	-.521*** (.071)	-.778*** (.218)
Head Roll (in 100)	-.148 (.082)	-.161 (.095)	.068 (.110)	.034 (.082)	-.099 (.252)

*Dependent variable:*

	<b>Adventurous (1)</b>	<b>Glamorous (2)</b>	<b>Smart (3)</b>	<b>Edgy (4)</b>	<b>Distant (5)</b>
Head Yaw (in 100)	.006 (.048)	.082 (.055)	-.126* (.064)	.020 (.048)	.018 (.147)
Exposure	-.197*** (.039)	.422*** (.045)	.120* (.053)	.124** (.039)	.207 (.120)
Blur	.054* (.026)	-.136*** (.030)	-.053 (.035)	-.104*** (.026)	-.349*** (.080)
Noise	-.030 (.025)	-.122*** (.029)	-.011 (.033)	-.053* (.025)	-.142 (.076)
Height-to-Width Ratio	.564 (.437)	-1.410** (.504)	1.941*** (.583)	.312 (.434)	-1.243 (1.333)
Happiness	.075*** (.015)	.102*** (.017)	-.172*** (.020)	-.063*** (.015)	-.286*** (.045)
Anger	.401*** (.104)	-.718*** (.120)	-.023 (.139)	.119 (.103)	-1.214*** (.317)
Contempt	.178 (.116)	-.950*** (.134)	-.252 (.155)	.103 (.115)	-1.498*** (.354)
Disgust	.678 (.361)	-.874* (.416)	-1.092* (.481)	-.142 (.358)	2.656* (1.100)
Fear	.008 (.429)	-.127 (.495)	-.018 (.572)	.127 (.426)	.279 (1.308)
Sadness	.369** (.113)	-1.112*** (.130)	.094 (.151)	.012 (.112)	-.858* (.345)
Surprise	.156 (.089)	-.775*** (.103)	-.151 (.119)	-.194* (.089)	-1.088*** (.272)
Number of Followers (ln)	-.079*** (.007)	.102*** (.008)	-.022* (.009)	-.062*** (.007)	-.064** (.021)
Number of Friends (ln)	.058*** (.010)	-.173*** (.011)	-.086*** (.013)	.037*** (.009)	.281*** (.029)
Number of Likes (ln)	.083*** (.003)	.029*** (.004)	.067*** (.004)	-.007* (.003)	-.086*** (.010)
Number of Statuses (ln)	-.031*** (.004)	-.094*** (.005)	-.067*** (.006)	.046*** (.004)	-.063*** (.013)
Brand Count (ln)	-.318*** (.008)	.224*** (.010)	.231*** (.011)	-.101*** (.008)	.239*** (.025)
Observations	62,799	62,799	62,799	62,799	62,799
R <sup>2</sup>	.055	.048	.026	.021	.018
F Statistic	126.254***	110.042***	56.705***	47.392***	38.774***

*Note.* Standard errors in parentheses.  $p < .05$  \*,  $p < .01$  \*\*,  $p < .001$  \*\*\*.

### **Study 3 Extension: Additional Application of the Framework**

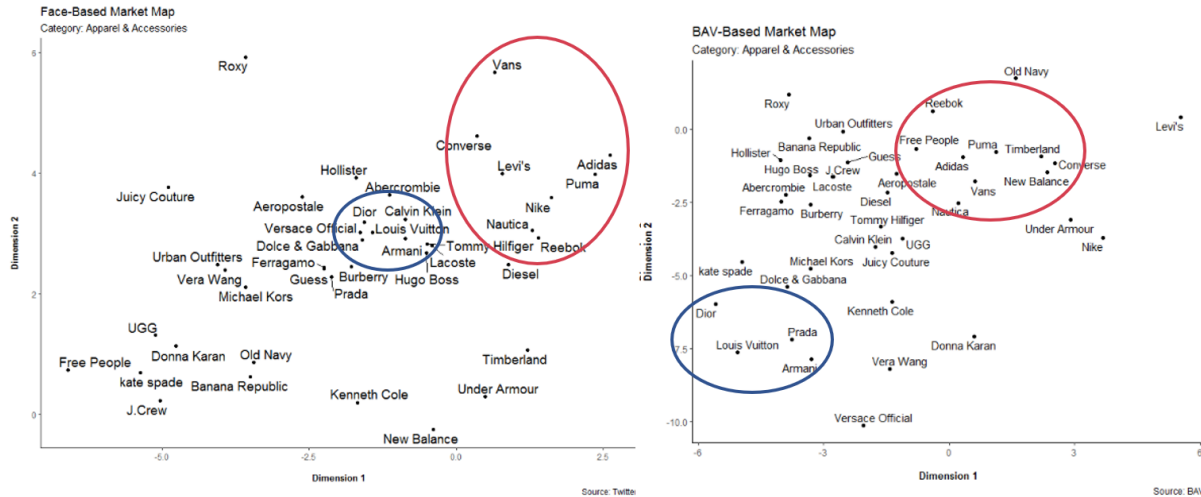
Having established which specific facial appearance characteristics align with distinct brand personality traits, we next demonstrate how this framework can be leveraged for an additional application. Beyond predicting individual brand preferences, the same face-based approach can be used to map relationships between brands, illustrating how our framework can move beyond prediction to offer tools for understanding market structure and consumer segments based solely on visual information.

For this purpose, we created face-based market maps using PCA on brand-level aggregated data, a standard approach for creating market maps (alongside multidimensional scaling on pairwise brand distances; Netzer et al. 2012). Specifically, for each brand, we first computed the mean values for all 27 facial appearance characteristics of its followers. We then applied PCA to this brand-by-characteristic matrix (N=444 brands \* 27 features) and plotted brands based on the first two principal components.

Focusing anecdotally on the apparel and accessories category, this analysis produced coherent brand clusters that mirrored known market structure: luxury brands clustered together, sports brands such as Nike and Puma appeared near each other, and outdoor brands such as Timberland and Under Armour were positioned close to one another (see figure 8). To validate this approach, we created a parallel brand map using the 47 BAV personality ratings, whose dimensionality we also reduced using PCA following the identical procedure as for the face-based market maps. The spatial distances between brands in the face-based map were positively correlated with those in the BAV-based map ( $r = .12, p < .001$ ), supporting the ability of consumer faces to recover meaningful brand relationships.

**FIGURE 8**

**COMPARISON BETWEEN FACE-BASED VS. BAV-BASED MARKET MAPS**



*Note.* The left panel presents the face-based market map and the right panel presents the BAV-based market map, both for the apparel and accessories category. Spatial proximity indicates greater similarity in follower facial characteristics (left) or brand personality dimensions (right).

**GENERAL DISCUSSION**

Communication among consumers, but also between consumers and brands, is becoming increasingly visual. While most marketing research employing automatic analyses of unstructured data has focused on text, only recently have researchers begun to explore the information contained in images (Witte et al. 2026). Contributing to this emerging stream, we ask whether faces, long considered a window into our identity (Zebrowitz 1997), can also be a mirror of our brand preferences. To address this question, we analyze a large-scale dataset of Twitter profile images and users' revealed brand preferences, as indicated by brand followership.

Our results demonstrate that faces convey meaningful information about consumer-brand relationships.

We first demonstrate that brand preferences across a wide range of industries can be predicted based on facial appearance alone. Using only a user's facial profile image, we can accurately predict whether they prefer Pepsi or Coke, root for the Knicks or the Brooklyn Nets, read the New York Times or the New York Post, or buy their groceries at Trader Joe's or Whole Foods Market.

Building on this foundation, we explore how prediction accuracy is systematically related to brand identity, as measured by brand personality dimensions. Specifically, prediction improves when two competing brands differ strongly in identity. This pattern is consistent with an identity-based account: because both facial appearance and brand preferences reflect underlying identity signals, brands with more distinct identities tend to attract consumers who look more different from each other, whereas brands with overlapping personalities tend to attract consumers with more similar facial appearance characteristics.

Next, we zoom in and examine the specific facial characteristics associated with particular brand personality traits. We find, for example, that "smart" brands, seen as intelligent, trustworthy, and reliable, are more likely to attract users with stereotypically related accessories such as reading glasses, while "glamorous" brands attract users who wear more make-up and sunglasses. Notably, beyond facial accessories, we also find systematic differences in emotional expressions: followers of smart and adventurous brands tend to appear happier, while those who prefer distant brands show more expressions of disgust. Followers of edgy brands, by contrast, express fewer emotions overall. Consistent with these feature-level results, face-based brand maps revealed coherent clusters (e.g., luxury, sports, outdoor brands) that closely mirrored

traditional BAV-based brand maps, demonstrating the framework's ability to segment brands on the faces of their audiences.

Taken together, these findings demonstrate the potential of automated face-based audience analytics. Not only do consumers' facial appearance characteristics predict brand preferences, but the predictive power is grounded in meaningful connections between facial self-presentation and brand identity. Our research highlights how faces can reflect the brands consumers endorse.

### **Contribution**

First, our findings contribute to the emerging research stream around visual information in marketing, by showing how information about consumers can be extracted from their faces and how their facial appearance characteristics can inform us about their brand preferences. To the best of our knowledge, we are the first to show that brand preferences can be predicted from one's face. Second, by revealing the face-brand association, this work contributes to the branding literature by introducing facial appearance as a predictive and identity-relevant signal of brand preference, thereby deepening our understanding of how consumers express identity through both brand affiliations and curated online visuals. Third, our findings contribute to the literature on faces by demonstrating that faces can reveal not only psychological traits but also marketplace preferences. While prior research has focused on examining who a person is from their face, our work shows that we can also infer what they like.

Finally, our results offer important implications for marketers, firms, and platforms. By analyzing the facial appearance of their followers on social media, advertisers and firms can first understand which brand dimensions resonate with different consumer segments and then target

users that align with their “brand type” but are not yet followers, and likely not yet customers, of their brand. While predictive accuracy at the individual level is modest, aggregate effects across large populations can be substantial. When behavioral data are absent, even small improvements over chance are valuable compared to no prediction at all. The face of the customer is one of the first signals observed by marketers at the start of the relationship with the customer or even at lead phase, thus offering a solution to the “cold start” problem. This approach could be applied broadly across industries; for example, in the travel sector, facial information could help reveal whether a person is more inclined toward casual or luxury travel, or towards brands with a down-to-earth versus glamorous appeal. Notably, such predictions are possible even for challenging cases involving canonical rivals. Beyond targeting individual consumers, our framework can also be used to build face-based brand market maps and consumer segment profiles, providing visually grounded insights into market structure and brand audiences.

Social media platforms could also leverage facial appearance to recommend brands to users whose preferences are not known yet. While other signals such as friends, followers, or other followed brands can also predict consumer interests, they are often more complex to collect and interpret, and their availability depends heavily on users’ activity levels. Profile images, by contrast, are typically present from the moment a user joins regardless of engagement. This enables platforms and marketers to predict initial brand preferences and deliver tailored brand recommendations and advertising, well before any activity-based data accumulates.

However, the same predictive power that benefits marketers and firms also raises important privacy concerns for consumers. Notably, our approach does not rely on collecting or storing historical behavioral data—predictions can be made based solely on a user’s current profile picture. Moreover, all results we report are on the aggregate level and thus do not allow

any inferences about individual users. Still, our findings carry implications not only for businesses but also for policymakers and individuals, emphasizing the need to consider how various forms of shared information can reveal sensitive aspects of personal identity.

## **Limitations**

There are, of course, limitations to our approach. First, notably, our analysis is correlational in nature. As such, we cannot determine the directionality: Do brands with a certain personality attract a certain consumer, or does the typical appearance of a brand's followers contribute to shaping how the brand is perceived (e.g., as intelligent or glamorous)? We encourage future research to examine this. Second, brand followership is only a proxy for brand preference. While most consumers follow the brands they like, some consumers may follow brands due to other motivations, such as industry monitoring. While we address these concerns by using a large sample of users and restricting our analyses to users that follow only one competing brand, it is still possible that some brand followership of users in our data does not represent true preferences. Third, we used only one facial image per user. However, firms with access to multiple images of consumers could develop more accurate predictions by aggregating facial characteristics across multiple photos, potentially reducing measurement error and capturing a more comprehensive representation of consumers' self-presentation. Finally, potential consumer privacy concerns must be considered and regulations should require the careful implementation of consumer analyses.

Despite these limitations, we hope our findings encourage future research on the opportunities and challenges of automated face analytics, particularly as social media research increasingly shifts from verbal to visual data.

## APPENDIX A

### 41 CATEGORIES IN SAMPLE

<b>Category</b>	<b>N</b>
Television Stations	39
Automobiles	27
Internet Tools and Services	26
Fast Food & Restaurant Chains	23
Football Events & Organizations	21
Specialty Retail Stores	19
Charity & Non-Profit Organizations	18
Computers & Computer Related Products	17
Department Stores & Mass Merchandisers	17
Sports & Casual Clothing	17
Assorted Financial Services	15
Beauty Products for the Face, Skin & Nails	14
Fashion Designers	14
Clothing & Footwear Retailers	13
Internet News/Information	12
Internet Commerce Service	11
Banks	9
Hotels & Motels	9
Industrial Corporations	9
Internet Commerce Retail	9
Sport & Leisure Shoes	9
Airlines	8
Consumer Electronics such as Stereos, TVs & VCRs	7
Magazines & Newspapers (General Interest)	7
Beers	6
Telecommunications Companies	5
Consulting Firms	4
Internet Communication	4
Pharmaceutical Companies	4
Supermarkets, Hypermarkets & Convenience Stores	4
Basketball Events & Organizations	3
Carbonated Soft Drinks	3
Extreme Sports Clothing & Equipment	3
Film Studios & Entertainment Companies	3
Gasoline/Petroleum	3
Internet Search	3
Magazines & Newspapers (Business & Personal Finance)	3
Magazines & Newspapers (Newsweeklies)	3
Spirits & Liquors	3
Internet Finance	2
Sporting Equipment	2

*Note.* The sample excludes 16 categories containing only a single brand, leaving 428 brands in total.

## APPENDIX B

### EXEMPLARY TWITTER FAN PAGE



The image shows a screenshot of the Coca-Cola Twitter profile page. At the top, there is a red header banner with the text "Share Hope" in white, and the Coca-Cola logo on the left. Below the banner, the profile name "Coca-Cola" and handle "@CocaCola" are visible, along with a verified account icon. The bio reads "Wherever we see hope, we're sharing it. #ShareHope" and "Biografie abstimmen". Location information "Atlanta, GA" and website "CocaCola.com/4gBwa" are also present. The follower count is "60.000 Folge" and "3,3 Mio. Follower". Below the profile information, a list of followers is displayed, each with a profile picture, name, handle, and a "Folgen" button.

**Share Hope**

**Coca-Cola** 

@CocaCola

Wherever we see hope, we're sharing it. #ShareHope  
Biografie abstimmen

Atlanta, GA [CocaCola.com/4gBwa](https://www.coca-cola.com/4gBwa) Seit März 2022 bei Twitter

60.000 Folge **3,3 Mio.** Follower

-  **Willy**  @willy1988  
May 1988 in Wien 
-  **Wolfgang**  @wolfgang1988  
Jan 1988 in Wien 
-  **Elisabeth**  @elisabeth1988  
Jan 1988 in Wien 
-  **Willy**  @willy1988  
Folgen Sie mir 
-  **Wolfgang**  @wolfgang1988  
Folgen Sie mir 
-  **Willy**  @willy1988  
Folgen Sie mir 
-  **Wolfgang**  @wolfgang1988  
Folgen Sie mir 
-  **Willy**  @willy1988  
Folgen Sie mir 
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Folgen Sie mir 
-  **Willy**  @willy1988  
Folgen Sie mir 
-  **Wolfgang**  @wolfgang1988  
Folgen Sie mir 
-  **Willy**  @willy1988  
Folgen Sie mir 
-  **Wolfgang**  @wolfgang1988  
Folgen Sie mir 

## APPENDIX C

### SUMMARY STATISTICS OF FACIAL APPEARANCE CHARACTERISTICS

<b>Variable</b>	<b>Min</b>	<b>1st Qu.</b>	<b>Median</b>	<b>Mean</b>	<b>3rd Qu.</b>	<b>Max</b>
Age (in 10 Yrs)	0.000	2.300	2.900	2.964	3.500	7.200
Is Women	0.000	0.000	0.000	0.486	1.000	1.000
Wears Reading Glasses	0.000	0.000	0.000	0.128	0.000	1.000
Wears Sun Glasses	0.000	0.000	0.000	0.066	0.000	1.000
Wears Eye Makeup	0.000	0.000	1.000	0.515	1.000	1.000
Wears Lip Makeup	0.000	0.000	0.000	0.433	1.000	1.000
Beard	0.000	0.000	0.000	0.122	0.100	0.900
Sideburns	0.000	0.000	0.000	0.082	0.100	0.900
Baldness	0.000	0.030	0.080	0.130	0.160	0.800
Has Blond Hair	0.000	0.000	0.000	0.106	0.000	1.000
Has Black Hair	0.000	0.000	0.000	0.432	1.000	1.000
Has Gray Hair	0.000	0.000	0.000	0.035	0.000	1.000
Has Red Hair	0.000	0.000	0.000	0.014	0.000	1.000
Head Pitch (in 100)	-0.844	-0.094	-0.039	-0.037	0.018	0.433
Head Roll (in 100)	-0.792	-0.048	-0.020	-0.001	0.044	0.630
Head Yaw (in 100)	-0.952	-0.079	-0.007	-0.009	0.063	0.932
Exposure	0.000	0.530	0.630	0.613	0.700	1.000
Blur	0.000	0.000	0.140	0.218	0.350	1.000
Noise	0.000	0.000	0.080	0.196	0.320	1.000
Height-to-Width Ratio	0.703	1.000	1.000	1.001	1.000	1.497
Happiness	0.000	0.003	0.771	0.551	1.000	1.000
Anger	0.000	0.000	0.000	0.005	0.000	1.000
Contempt	0.000	0.000	0.000	0.009	0.001	1.000
Disgust	0.000	0.000	0.000	0.001	0.000	0.937
Fear	0.000	0.000	0.000	0.001	0.000	0.994
Sadness	0.000	0.000	0.000	0.009	0.001	1.000
Surprise	0.000	0.000	0.000	0.009	0.000	1.000

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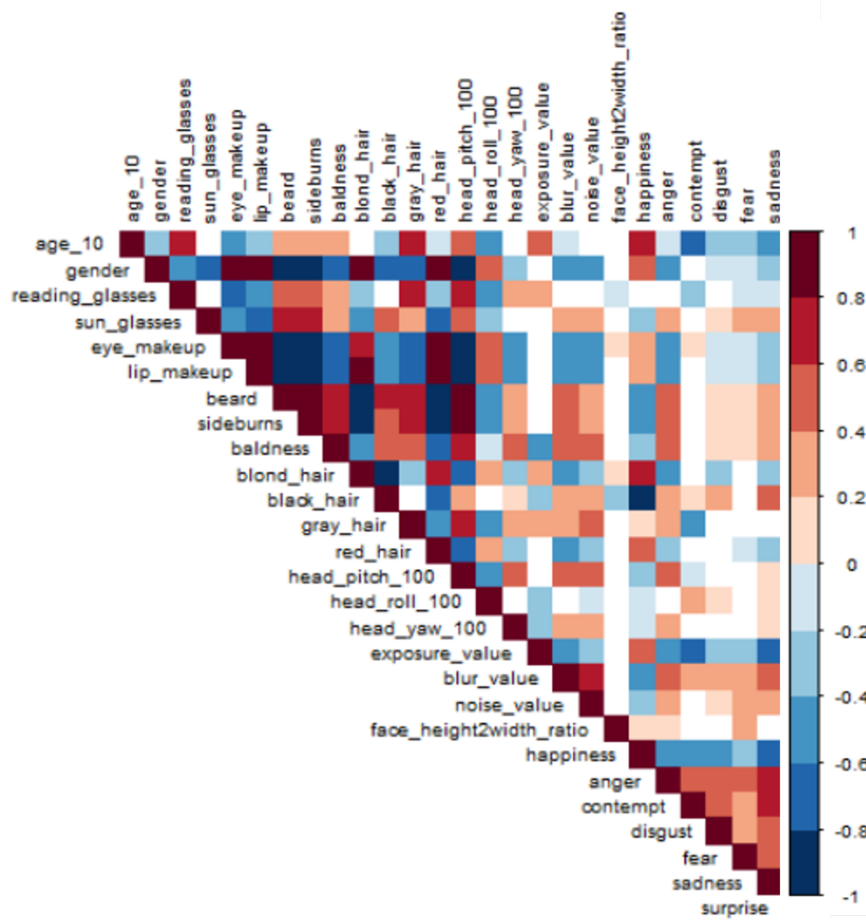
# **We Look Like What We Like**

## **WEB APPENDIX**

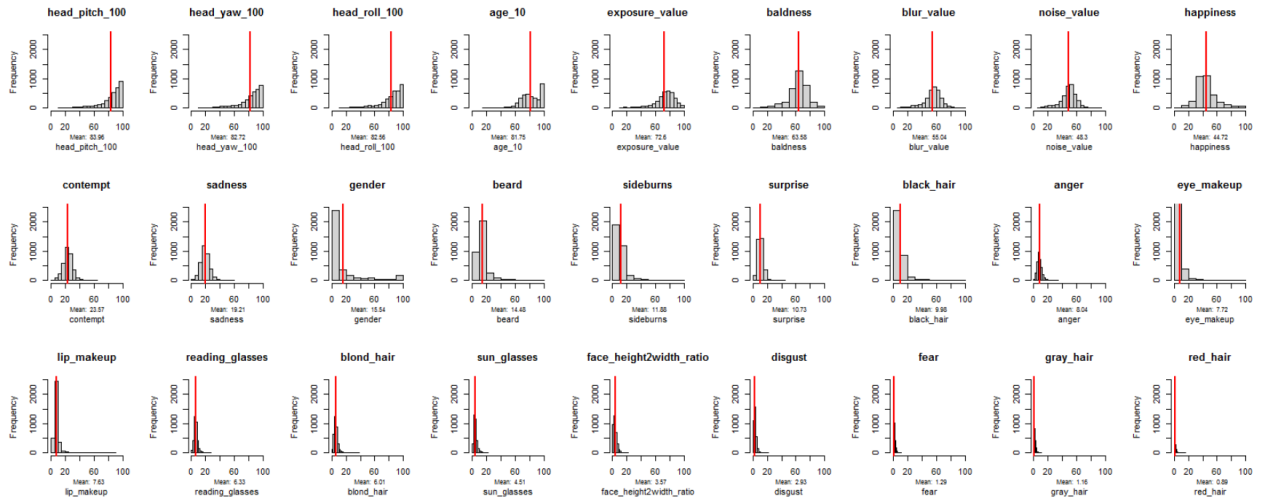
## **Web Appendix A: Random Forest Training Procedure**

Our implementation used R's `caret` and `ranger` packages to execute the random forest algorithm. For each brand pair, we filtered the dataset to include only users who followed exactly one of the two brands. We then balanced the classes by sampling up to 250 users per brand to ensure equal representation. To handle potential data leakage, we first partitioned each dataset with `createDataPartition()` function, ensuring stratified sampling by brand class. The hyperparameter tuning process used `trainControl()` with fixed seeds for reproducibility. We employed impurity-based variable importance measurement (`importance = "impurity"`) to assess feature contributions. For evaluation, we generated confusion matrices using `confusionMatrix()` and extracted overall accuracy metrics. User overlap between brands was calculated and recorded alongside performance metrics. The final output for each brand pair included sample sizes (before and after capping), user overlap percentage, mean accuracy, standard deviation, and standard error across the five runs.

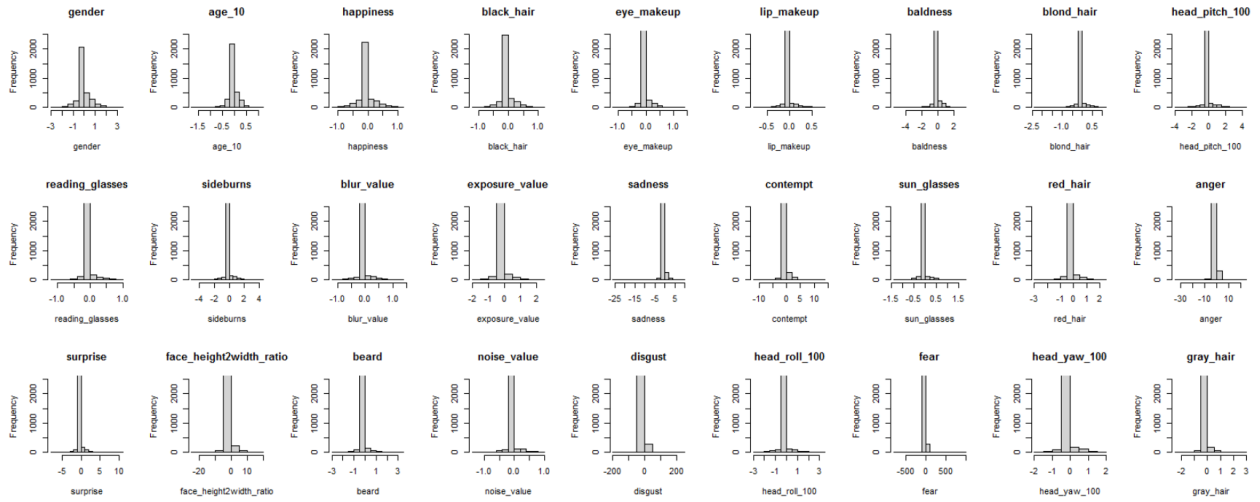
## Web Appendix B: Correlation Matrix of Facial Appearance Characteristics (Study 1)



# Web Appendix C: Histograms of Random Forest Variable Importance (Study 1)



## Web Appendix D: Histograms of LASSO Coefficients (Study 1)

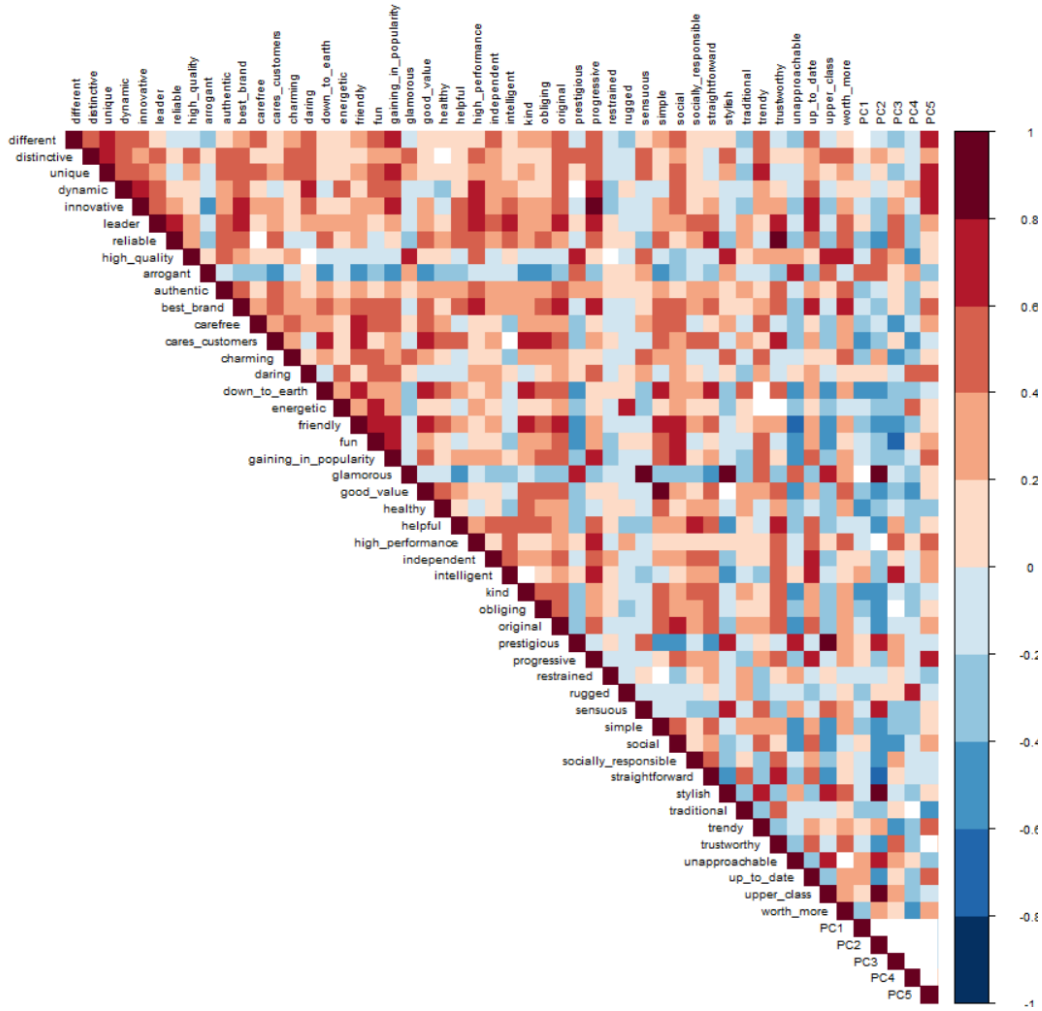


**Web Appendix E: Summary Statistics of 47 BAV Dimensions (Study 2)**

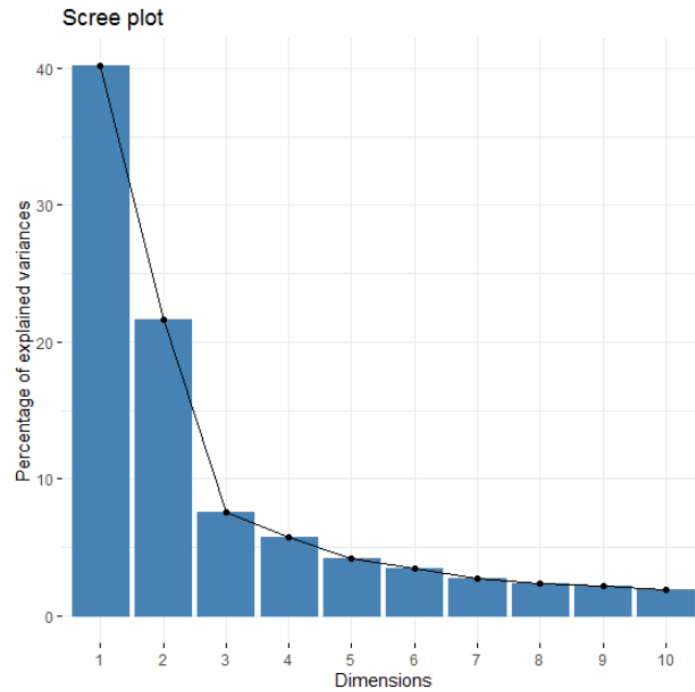
<b>Variable</b>	<b>Min</b>	<b>1st Qu.</b>	<b>Median</b>	<b>Mean</b>	<b>3rd Qu.</b>	<b>Max</b>
different	2.675	7.125	8.678	9.292	11.031	24.171
distinctive	3.482	10.092	12.080	12.710	15.031	23.371
unique	3.059	7.352	9.161	9.889	11.862	23.524
dynamic	3.002	7.451	9.379	9.794	11.793	21.604
innovative	2.786	7.530	9.856	10.602	12.912	26.831
leader	4.427	11.177	14.264	15.153	17.841	33.166
reliable	3.582	10.411	14.121	14.622	18.056	35.522
high_quality	2.723	10.448	14.068	15.958	20.356	43.732
arrogant	0.623	3.546	5.221	6.319	8.277	27.247
authentic	2.910	9.001	10.648	10.990	12.768	21.729
best_brand	0.457	4.484	6.179	7.063	8.889	21.766
carefree	1.082	4.887	6.314	6.510	7.873	14.455
cares_customers	3.473	8.453	10.635	11.367	13.512	33.455
charming	1.155	4.596	6.241	6.759	8.183	24.860
daring	1.761	5.687	7.430	7.964	9.486	21.557
down_to_earth	3.250	10.590	13.820	15.220	18.550	37.590
energetic	3.192	6.777	8.503	9.253	10.993	21.816
friendly	3.282	9.541	12.670	14.019	16.872	35.236
fun	1.174	6.767	10.627	12.993	17.537	45.881
gaining_in_popularity	1.838	5.642	7.404	7.974	9.687	21.482
glamorous	0.722	4.485	5.621	7.539	8.314	31.282
good_value	2.843	7.921	10.799	12.693	16.042	41.540
healthy	0.928	3.521	4.819	6.009	6.970	38.964
helpful	2.421	6.510	9.103	10.402	12.949	37.177
high_performance	3.244	7.073	9.349	10.295	12.065	29.388
independent	2.447	8.800	10.256	10.387	11.742	20.059
intelligent	2.896	7.837	10.406	11.600	14.512	32.648
kind	1.933	5.657	7.297	7.747	9.190	25.816

<b>Variable</b>	<b>Min</b>	<b>1st Qu.</b>	<b>Median</b>	<b>Mean</b>	<b>3rd Qu.</b>	<b>Max</b>
obliging_num	1.916	5.367	6.812	6.909	8.215	13.189
original	5.324	12.909	15.599	16.399	19.106	32.921
prestigious	1.999	5.293	7.031	8.544	9.811	29.685
progressive	1.534	6.114	7.667	8.127	9.446	20.566
restrained_num	0.931	4.233	5.237	5.312	6.337	11.730
rugged	1.541	4.188	5.429	6.916	7.536	30.011
sensuous	0.434	2.629	3.541	4.121	4.904	26.709
simple	3.695	9.947	12.582	13.193	15.546	34.389
social	2.164	10.345	13.096	13.644	16.365	36.326
socially_responsible	1.812	7.652	9.177	9.740	10.984	31.894
straightforward	1.907	8.033	9.556	9.876	11.599	18.902
stylish	1.699	5.102	6.739	9.883	13.683	38.623
traditional	0.000	6.741	8.787	9.582	12.093	24.662
trendy	3.203	9.108	12.613	13.946	18.015	34.278
trustworthy	4.394	11.002	14.900	15.340	19.019	36.220
unapproachable	0.000	3.997	5.072	5.636	6.894	17.709
up_to_date	3.254	9.560	11.826	12.248	14.435	23.367
upper_class	2.101	5.294	7.111	9.480	10.774	39.187
worth_more	0.691	4.022	6.090	6.470	8.363	21.701

# Web Appendix F: BAV Correlation Matrix (Study 3)



## Web Appendix G: Scree Plot for BAV Dimensions (Study 3)



*Note.* The scree plot suggests a bend around the fifth component, after which the explained variance levels off. On this basis, retaining five principal components seems a reasonable balance between capturing variance and avoiding overfitting.

## Web Appendix H: Regression with 47 Raw BAV Dimensions (Study 3)

	temply (1)	glamorous (2)	intelligent (3)	stylish (4)	sensuous (5)	charming (6)	fun (7)	friendly (8)	helpful (9)
Age (in 10 Yrs)	-1.37*** (.04)	-.756*** (.03)	1.23*** (.03)	-1.36*** (.05)	-.27*** (.02)	-.32*** (.02)	-2.25*** (.06)	-.60*** (.04)	1.31*** (.04)
Is Female	4.13*** (.12)	3.47*** (.10)	-2.71*** (.09)	3.88*** (.14)	1.57*** (.04)	2.22*** (.06)	1.39*** (.17)	3.55*** (.13)	.79*** (.10)
Wears Reading Glasses	-.44*** (.11)	-.81*** (.10)	-.81*** (.08)	-1.06*** (.13)	-.28*** (.04)	-.09 (.06)	.06 (.16)	.41*** (.12)	.47*** (.10)
Wears Sun Glasses	.39** (.15)	.22 (.13)	.22* (.11)	.84*** (.17)	-.01 (.06)	-.03 (.08)	-.43* (.21)	-.46** (.16)	-.17 (.13)
Wears Eye Makeup	1.32*** (.10)	1.29*** (.09)	-.77*** (.07)	1.66*** (.11)	.40*** (.04)	.34*** (.05)	.33* (.14)	-.23* (.11)	-.94*** (.09)
Wears Lip Makeup	.67*** (.10)	1.29*** (.08)	-.43*** (.07)	1.23*** (.11)	.42*** (.04)	.24*** (.05)	-.48*** (.13)	-.45*** (.10)	-.54*** (.08)
Band	21 (.33)	-.79*** (.28)	1.13*** (.24)	-.69 (.37)	.08 (.12)	.03 (.17)	.54 (.46)	.29 (.36)	.44 (.29)
Sidburns	-.07 (.44)	.01 (.37)	.28 (.32)	.001 (.49)	-.09 (.16)	-.23 (.22)	1.10 (.61)	-.60 (.47)	-.62 (.38)
Baldness	-.31 (.25)	.44* (.21)	-.44*** (.18)	-.004 (.28)	.15 (.09)	-.06 (.12)	.20 (.35)	.19 (.27)	-.39 (.21)
Has Blond Hair	.49*** (.13)	.19 (.11)	-.17 (.09)	.46** (.14)	.06 (.05)	.32*** (.06)	.71*** (.18)	.80*** (.14)	.29** (.11)
Has Black Hair	-.50*** (.08)	.11 (.07)	-.07 (.06)	.19* (.09)	-.001 (.03)	-.42*** (.04)	-.202*** (.11)	-.170*** (.09)	-.28*** (.07)
Has Gray Hair	.54* (.22)	.84*** (.19)	1.50*** (.16)	1.00*** (.24)	.27*** (.08)	-.07 (.11)	.76* (.30)	-.45 (.23)	1.68*** (.19)
Has Red Hair	.09 (.31)	-.32 (.26)	.33 (.23)	-.31 (.34)	-.01 (.11)	.33* (.15)	1.04* (.43)	1.10*** (.33)	.65* (.26)
Head Puck (in 100)	-2.45*** (.43)	-3.15*** (.36)	.38 (.31)	-3.52*** (.48)	-.94*** (.16)	-.48* (.21)	2.63*** (.59)	2.40*** (.46)	1.33*** (.37)
Head Roll (in 100)	.81* (.40)	1.20*** (.34)	-.57 (.30)	1.47*** (.45)	.33* (.15)	.39 (.20)	.66 (.56)	.01 (.43)	-.62 (.35)
Head Yaw (in 100)	-.22 (.26)	-.68*** (.22)	.21 (.19)	-.59* (.29)	-.23* (.10)	-.07 (.13)	.44 (.36)	.40 (.28)	.19 (.22)
Exposure	.18 (.23)	.38* (.19)	1.25*** (.17)	.65* (.25)	.14 (.08)	-.04 (.11)	-.2.96*** (.31)	-.89*** (.24)	1.19*** (.19)
Blur	.34* (.15)	-.27* (.13)	-.43*** (.11)	.01 (.17)	-.06 (.06)	.16* (.08)	1.45*** (.21)	.91*** (.16)	-.14 (.13)
Noise	.31* (.15)	.32*** (.12)	-.36*** (.11)	.38* (.16)	.08 (.05)	.19** (.07)	.45* (.20)	.35* (.16)	-.08 (.13)
Height-2:Width Ratio	4.44* (1.94)	4.22* (1.65)	-2.98* (1.43)	6.00** (2.17)	2.29** (.72)	-.96 (.97)	4.76 (2.71)	.06 (2.09)	-3.13 (1.68)
Happiness	-.96*** (.09)	-1.69*** (.07)	-.97*** (.06)	-1.75*** (.10)	-.66*** (.03)	-.22*** (.04)	-.12 (.12)	.86*** (.09)	1.28*** (.08)
Anger	1.95** (.73)	-1.21* (.62)	.29 (.54)	-.21 (.81)	-.11 (.27)	1.34*** (.36)	8.09*** (1.02)	4.59*** (.78)	.04 (.63)
Contempt	3.57*** (.69)	-.53 (.58)	-1.95*** (.51)	.91 (.77)	.07 (.25)	1.32*** (.34)	9.76*** (.96)	6.17*** (.74)	-1.04 (.59)
Disgust	-3.78 (2.19)	-6.32*** (1.85)	-5.15** (1.61)	-8.25*** (2.44)	-.2.64** (.81)	-2.95** (1.09)	2.66 (3.05)	-2.47 (2.35)	-3.06 (1.89)
Fear	-1.21 (2.50)	-2.14 (2.12)	-1.89 (1.84)	-2.69 (2.79)	-.89 (.92)	-1.69 (1.25)	5.15 (3.48)	-.49 (2.68)	-4.35* (2.16)
Sadness	1.80** (.68)	-1.74** (.58)	-1.30** (.50)	-.67 (.76)	-.80** (.25)	.51 (.34)	7.30*** (.95)	2.73*** (.73)	-1.53** (.59)
Surprise	1.07* (.51)	-1.08* (.43)	-.88* (.38)	-.51 (.57)	-.38* (.19)	.55* (.26)	4.96*** (.72)	2.89*** (.55)	-.34 (.44)
Number of Followers (ln)	-.04 (.04)	-.37*** (.03)	.61*** (.03)	-.35*** (.04)	-.16*** (.01)	-.11*** (.02)	-1.27*** (.06)	.001 (.04)	.99*** (.03)
Number of Friends (ln)	-.91 *** (.04)	.17*** (.04)	-.49*** (.03)	-.003 (.05)	-.07*** (.02)	-.29*** (.02)	-.98*** (.06)	-1.03*** (.05)	-.87*** (.04)
Number of Likes (ln)	-.14*** (.02)	-.03* (.02)	.02 (.01)	-.04* (.02)	-.01 (.01)	-.01 (.01)	.45*** (.02)	-.05** (.02)	.35*** (.02)
Number of Shares (ln)	.70*** (.02)	.10*** (.02)	-.18*** (.02)	.23*** (.03)	.07*** (.01)	.19*** (.01)	.82*** (.03)	.68*** (.03)	.08*** (.02)
Observations	122,161	122,161	122,161	122,161	122,161	122,161	122,161	122,161	122,161
R <sup>2</sup>	.08	.08	.08	.07	.07	.06	.05	.04	.04
F Statistic	357.99***	339.69***	318.52***	289.20***	276.23***	260.11***	197.23***	176.80***	167.78***

	high performance (10)	missed (11)	socially responsible	gaining in popularity	cares customers (14)	entree (15)	healthy (16)	kind (17)	social (18)	energetic (19)	dynamic (20)
	-20*** (.03)	-.04 (.03)	.76*** (.03)	-.06** (.02)	.39*** (.03)	-.29*** (.02)	.08** (.03)	.19*** (.02)	-.47*** (.03)	-.29*** (.03)	-.20*** (.02)
	-2.94*** (.09)	-2.06*** (.10)	1.13*** (.08)	.74*** (.07)	2.27*** (.10)	.86*** (.05)	1.55*** (.08)	1.65*** (.07)	1.56*** (.10)	-1.10*** (.09)	-1.58*** (.07)
	.04 (.09)	-.65*** (.10)	.18* (.07)	.19** (.06)	.20* (.09)	-.07 (.05)	-.06 (.08)	.20** (.06)	.03 (.09)	-.42*** (.08)	.02 (.07)
	.74*** (.11)	.65*** (.13)	-.02 (.10)	.18* (.08)	-.14 (.12)	.09 (.06)	-.12 (.10)	-.12 (.08)	-.35** (.12)	.05 (.11)	.25** (.09)
	-.34*** (.08)	-.56*** (.09)	-.47*** (.07)	.001 (.05)	-.30*** (.08)	.05 (.04)	-.40*** (.07)	-.27** (.06)	-.20* (.08)	-.40*** (.07)	-.16** (.06)
	-.22*** (.07)	-.35*** (.08)	-.22*** (.06)	-.14** (.05)	-.17* (.08)	.03 (.04)	-.06 (.06)	-.16*** (.05)	-.40*** (.08)	-.38*** (.07)	-.14* (.05)
	.90*** (.25)	.21 (.28)	.10 (.21)	.28 (.18)	.04 (.26)	.19 (.14)	-.31 (.22)	.21 (.19)	.30 (.26)	-.004 (.23)	.65*** (.19)
	.56 (.33)	1.01** (.37)	.34 (.28)	.50* (.24)	-.19 (.35)	.15 (.19)	.17 (.29)	-.22 (.24)	.22 (.35)	.74* (.31)	.64* (.25)
	-.71*** (.19)	.78*** (.21)	-.13 (.16)	-.52*** (.13)	.42* (.20)	-.002 (.11)	.38* (.17)	.05 (.14)	.11 (.20)	.99*** (.17)	-.49*** (.14)
	.17 (.10)	.53*** (.11)	.43*** (.08)	.35*** (.07)	.49*** (.10)	.20*** (.05)	.46*** (.08)	.37*** (.07)	.43*** (.10)	.46*** (.09)	.19** (.07)
	-.33*** (.06)	-.99*** (.07)	-.71*** (.05)	-.68*** (.04)	-.92*** (.07)	-.47*** (.04)	-.79*** (.05)	-.61*** (.05)	-.102*** (.07)	-.104*** (.06)	-.45*** (.05)
	-.53** (.16)	-.25 (.18)	-.104*** (.14)	-.54*** (.12)	-.105*** (.17)	-.10 (.09)	-.64*** (.15)	-.59*** (.12)	-.17 (.17)	-.20 (.15)	-.39** (.12)
	.12 (.23)	.002 (.26)	.38 (.20)	.40** (.17)	.58* (.24)	.15 (.13)	.27 (.20)	.43* (.17)	.69** (.24)	.31 (.22)	.34 (.17)
	.69* (.32)	2.24*** (.36)	.95*** (.28)	-.06 (.23)	1.359*** (.34)	.30 (.18)	.91** (.28)	.71** (.24)	1.40*** (.34)	2.29*** (.30)	.53* (.24)
	.28 (.30)	-.20 (.34)	-.41 (.26)	-.16 (.22)	.09 (.32)	-.07 (.17)	-.05 (.27)	-.09 (.22)	-.16 (.32)	-.16 (.28)	-.01 (.23)
	.22 (.20)	.35 (.22)	.11 (.17)	.19 (.14)	.16 (.20)	.10 (.11)	.16 (.17)	.21 (.14)	.07 (.21)	.31 (.18)	.24 (.15)
	.48** (.17)	-.62** (.19)	.27 (.15)	.03 (.12)	.18 (.18)	-.14 (.10)	-.19 (.15)	.02 (.13)	-.83*** (.18)	-.111*** (.16)	-.04 (.13)
	.04 (.12)	.71*** (.13)	.06 (.10)	.19* (.08)	.30** (.12)	.22*** (.07)	.42*** (.10)	.25*** (.09)	.59*** (.12)	.57*** (.11)	.17 (.09)
	-.06 (.11)	.02 (.12)	-.04 (.09)	.04 (.08)	.13 (.11)	.10 (.06)	.09 (.10)	.06 (.08)	.31** (.11)	.17 (.10)	-.01 (.08)
	-.46 (.47)	1.38 (1.64)	-.12 (1.26)	.84 (1.05)	-.54 (1.54)	.43 (.83)	-.80 (1.29)	-.48 (1.09)	1.04 (1.54)	1.09 (1.37)	1.22 (1.11)
	.26*** (.07)	.62*** (.07)	.86*** (.06)	.39*** (.05)	.80*** (.07)	.05 (.04)	.39*** (.06)	.47*** (.05)	.38*** (.07)	.52*** (.05)	.20*** (.05)
	1.04 (.55)	2.29*** (.61)	.86 (.47)	1.76*** (.39)	1.77*** (.58)	1.61*** (.31)	1.54** (.48)	1.29** (.41)	3.50*** (.58)	3.23*** (.51)	2.03*** (.42)
	1.16* (.52)	3.13*** (.58)	-.52 (.45)	2.31*** (.37)	2.02*** (.55)	2.60*** (.46)	2.60*** (.46)	1.73*** (.39)	3.98*** (.55)	3.36*** (.48)	1.34*** (.39)
	-.412* (1.65)	.24 (1.85)	-.318* (1.42)	-.62 (1.18)	-.437* (1.73)	-.227* (.94)	-.237 (1.45)	-.3.46** (1.23)	.12 (1.73)	-.37 (1.54)	-.2.84* (1.25)
	-.30 (1.88)	1.68 (2.11)	-.1.80 (1.62)	-.23 (1.35)	-.2.66 (1.98)	-.41 (1.07)	3.03 (1.66)	-.1.70 (1.40)	-.1.92 (1.88)	2.10 (1.76)	1.00 (1.43)
	.22 (.51)	2.08*** (.57)	.61 (.44)	1.20** (.37)	.46 (.54)	.75* (.29)	.68 (.45)	.47 (.38)	2.87*** (.54)	2.77*** (.48)	1.13** (.39)
	.21 (.39)	2.10*** (.43)	.69* (.33)	.85** (.28)	1.10** (.41)	.88*** (.22)	1.46*** (.34)	.77** (.29)	2.00** (.41)	2.26*** (.36)	.71* (.29)
	-.07* (.03)	.12*** (.03)	.57*** (.03)	.13*** (.02)	.43*** (.03)	.05** (.02)	.42*** (.03)	.30*** (.02)	.02 (.03)	-.07* (.03)	.004 (.02)
	-.48*** (.03)	-.1.21*** (.04)	-.85*** (.03)	-.86*** (.02)	-.89*** (.04)	-.55*** (.02)	-.87*** (.03)	-.67*** (.02)	-.85*** (.04)	-.85*** (.03)	-.65*** (.03)
	.22*** (.01)	.43*** (.02)	.03* (.01)	.01 (.01)	-.03* (.01)	-.001 (.01)	.02 (.01)	-.04*** (.01)	-.08*** (.01)	.30*** (.01)	.18*** (.01)
	-.04* (.02)	-.04 (.02)	.03* (.02)	.37*** (.01)	.24*** (.02)	.25*** (.01)	.24*** (.02)	.18* (.01)	.54*** (.02)	.11*** (.02)	.06** (.01)
	122.161	122.161	122.161	122.161	122.161	122.161	122.161	122.161	122.161	122.161	122.161
	.04	.03	.03	.03	.03	.03	.03	.03	.03	.03	.03
	151.23***	137.51***	132.60***	127.04***	124.04***	122.53***	121.92***	119.65***	108.49***	107.92***	107.31***

	good value (21)	unique (22)	down to earth (23)	independent (24)	improviser (25)	different (26)	simple (27)	straightforward (28)	daring (29)	obliging (30)	progressive (31)
	-45*** (05)	-23*** (02)	.08 (.05)	.39*** (02)	-1.11*** (03)	-.02 (.02)	-.22*** (04)	.41*** (02)	-.13*** (02)	.23*** (02)	.23*** (02)
	2.91*** (13)	1.14*** (07)	2.75*** (14)	.53*** (06)	-1.89*** (09)	.90*** (07)	1.98*** (11)	.31*** (07)	-.58*** (06)	.64*** (05)	-.76*** (06)
	.50*** (13)	.04 (.07)	.10 (.13)	.07 (06)	.73*** (08)	.10 (06)	.19 (10)	-.03 (06)	-.16*** (06)	.02 (05)	.36*** (05)
	-.01 (17)	.17 (09)	-.14 (17)	.07 (08)	.34*** (11)	-.03 (08)	-.13 (14)	.07 (09)	.17* (08)	.02 (06)	.22*** (07)
	-43*** (11)	.25*** (06)	-.89*** (12)	-.28*** (05)	-.18* (07)	.02 (06)	-.55*** (09)	-.59*** (06)	.04 (05)	-.25*** (04)	-.24*** (05)
	-.39*** (11)	.13* (06)	-.67*** (11)	-.11* (05)	-.23*** (07)	-.01 (05)	-.34*** (09)	-.33*** (05)	.02 (05)	-.13*** (04)	-.17*** (05)
	.72* (37)	-.07 (20)	.50 (38)	.06 (18)	1.55*** (24)	.12 (19)	.60* (30)	.29 (19)	.25 (17)	.13 (14)	.53*** (16)
	-.68 (48)	.94*** (26)	-.75 (50)	.48* (23)	.58* (25)	.58* (25)	-.77 (40)	-.24 (25)	1.01*** (23)	-.17 (18)	.52* (21)
	.36 (28)	-.45** (15)	1.05*** (29)	-.03 (13)	-2.00*** (18)	-.13 (14)	.31 (23)	.53*** (14)	-.12 (13)	.05 (10)	-.89*** (12)
	.54*** (14)	.17* (08)	.90*** (15)	.23*** (07)	-.12 (09)	.19* (07)	.52*** (12)	.38*** (07)	.21*** (07)	.27*** (05)	.02 (06)
	-1.30*** (09)	-.59*** (05)	-1.68*** (09)	-.61*** (04)	-.20*** (06)	-.56*** (05)	-1.15*** (07)	-.76*** (05)	-.58*** (04)	-.42*** (03)	-.34*** (04)
	-.74*** (24)	-.24 (13)	-.99*** (25)	-.61*** (12)	-.80*** (16)	-.32* (12)	-.55*** (20)	-.77*** (11)	.08 (09)	-.59*** (10)	-.65*** (10)
	.64 (34)	.41* (19)	.94*** (35)	.40* (16)	.42 (23)	.45* (17)	.68* (28)	.33 (17)	.41* (16)	.38*** (13)	.30* (14)
	2.45*** (47)	-.98*** (26)	3.55*** (49)	.43 (23)	.38 (31)	-.17 (24)	2.14*** (39)	1.60*** (24)	-.13 (22)	.55*** (18)	-.05 (20)
	.38 (45)	.08 (24)	.03 (46)	-.23 (21)	-.03 (30)	-.30 (23)	.13 (37)	-.28 (23)	-.27 (21)	-.07 (17)	-.12 (19)
	.31 (29)	-.01 (16)	.59* (30)	.0002 (14)	.16 (19)	.07 (15)	.29 (24)	.19 (15)	.05 (14)	.03 (11)	.09 (12)
	-.24 (25)	.07 (14)	-.71*** (26)	.17 (12)	.86*** (17)	-.16 (13)	-.34 (21)	.01 (13)	-.25* (12)	.18 (09)	.53*** (11)
	.82*** (17)	.03 (09)	1.12*** (18)	.09 (08)	-.21 (11)	.13 (09)	.81*** (14)	.45*** (09)	.13 (08)	.15* (08)	-.10 (06)
	.39* (16)	.12 (09)	.28 (17)	-.004 (08)	-.15 (11)	.06 (08)	.31* (13)	.04 (08)	-.04 (08)	.06 (06)	-.05 (07)
	-1.62 (216)	2.31 (118)	-1.80 (223)	.35 (104)	-.99 (144)	1.42 (109)	-2.78 (177)	-1.65 (110)	2.37* (102)	-.57 (82)	-.68 (92)
	.60*** (10)	-.09 (05)	1.14*** (10)	.39*** (05)	.28*** (06)	.03 (05)	.55*** (08)	.66*** (35)	-.17 (35)	-.34*** (45)	.43*** (15)
	3.10*** (81)	1.95** (44)	3.94*** (83)	1.30*** (39)	1.25*** (54)	1.80*** (41)	2.50*** (66)	1.54*** (41)	2.04*** (38)	1.12*** (31)	.56 (34)
	4.91*** (76)	1.72*** (42)	5.82*** (79)	1.08** (37)	.91 (51)	1.94*** (39)	4.56*** (63)	1.65*** (39)	1.97*** (36)	.98*** (29)	.46 (32)
	-4.29 (243)	-3.69** (133)	-3.46 (251)	-2.62* (117)	-3.87* (162)	-3.22* (123)	-2.07 (199)	-1.70 (124)	-1.16 (115)	-2.22* (92)	-2.92** (103)
	-1.33 (277)	.10 (152)	-1.99 (286)	-1.52 (134)	.65 (185)	-.15 (141)	-.94 (228)	-1.77 (141)	.77 (131)	-1.19 (105)	.30 (118)
	1.31 (75)	.84* (41)	2.19** (78)	.48 (36)	-.10 (50)	.68 (38)	1.41* (62)	.72 (38)	1.21*** (36)	.10 (29)	.13 (32)
	1.70** (57)	.65* (31)	2.62*** (59)	.52 (27)	-.11 (36)	.64* (29)	1.27*** (47)	.82** (29)	.92*** (27)	.48* (22)	.19 (24)
	.04 (04)	.13*** (02)	.13* (05)	.35*** (02)	.30*** (02)	.24*** (02)	.18*** (02)	.25*** (02)	-.05* (02)	.27*** (02)	.27*** (02)
	-.65*** (05)	-.76*** (03)	-1.03*** (05)	-.80*** (02)	-.84*** (03)	-.88*** (03)	-.91*** (04)	-.68*** (03)	-.68*** (02)	-.54*** (02)	-.53*** (02)
	-.06** (02)	.04*** (01)	.08** (02)	.05*** (01)	-.07*** (02)	-.01 (01)	-.04* (02)	.04*** (01)	.26*** (01)	-.03*** (01)	.05*** (01)
	.64*** (03)	.25*** (01)	.47*** (03)	.16*** (01)	.22*** (02)	.29*** (02)	.50*** (02)	.16*** (01)	.06*** (01)	.14*** (01)	.06*** (01)
	122.161	122.161	122.161	122.161	122.161	122.161	122.161	122.161	122.161	122.161	122.161
	.03	.03	.02	.02	.02	.02	.02	.02	.02	.02	.02
	104.99***	104.30***	101.09***	100.00***	99.63***	99.18***	97.43***	94.65***	90.58***	89.90***	88.99***

restrained mean (S2)	reliable (S3)	trustworthy (S4)	original (S5)	up-to-date (S6)	traditional (S7)	distinctive (S8)	leader (S9)	workhorse (40)	upper class (41)	authentic (42)
.21*** (.01)	-.88*** (.04)	.83*** (.04)	-.24*** (.04)	.27*** (.02)	.22*** (.03)	-.16*** (.03)	.31*** (.04)	-.31*** (.02)	-.16*** (.04)	-.003 (.02)
.41*** (.04)	-1.10*** (.12)	-.02 (.12)	.70*** (.11)	.04 (.02)	.40*** (.09)	.41* (.08)	-1.17*** (.10)	.30*** (.06)	.30*** (.12)	.35*** (.07)
-.07 (.04)	.35*** (.11)	.37*** (.11)	.23* (.10)	-.10 (.07)	-.19* (.08)	-.28*** (.08)	.17 (.10)	.04 (.06)	-.76*** (.11)	-.08 (.07)
.04 (.05)	.38* (.15)	.25 (.15)	-.13 (.14)	-.10 (.09)	.05 (.11)	.37*** (.10)	.39*** (.13)	.38*** (.07)	.89*** (.15)	.27*** (.09)
-.20*** (.03)	-.94*** (.10)	-.82*** (.10)	-.39*** (.09)	-.31*** (.06)	-.0.62*** (.07)	.17* (.07)	-.56*** (.09)	.14** (.05)	.85*** (.10)	-.21*** (.06)
-.02 (.03)	-.54*** (.09)	-.51*** (.09)	-.36*** (.09)	-.20*** (.09)	-.0.29*** (.07)	.18* (.07)	-.38*** (.08)	.13** (.05)	.85*** (.09)	-.08 (.06)
.16 (.10)	.66** (.33)	.36 (.32)	.19 (.30)	.56*** (.20)	-.0.18 (.23)	-.38 (.23)	.27 (.28)	.43*** (.16)	-1.49*** (.32)	.14 (.20)
-.06 (.14)	-.60 (.43)	-.23 (.43)	.53 (.40)	.08 (.26)	.03 (.31)	.89* (.30)	.01 (.37)	-.01 (.22)	.90* (.42)	.31 (.27)
.36*** (.08)	-.13 (.25)	-.29 (.24)	-.18 (.23)	-.52*** (.15)	1.13*** (.18)	-.32 (.17)	-.39*** (.21)	-.23* (.12)	-.25 (.24)	.01 (.15)
.20*** (.04)	.37*** (.13)	.54*** (.12)	.47*** (.12)	.29*** (.08)	.56*** (.09)	.38*** (.09)	.25*** (.11)	.24*** (.06)	.11 (.12)	.32*** (.08)
-.34*** (.03)	-.70*** (.08)	-.83*** (.08)	-.132*** (.08)	-.53*** (.05)	-.0.99*** (.06)	-.71*** (.06)	-.78*** (.07)	-.32*** (.04)	.26*** (.08)	-.01*** (.05)
-.26** (.07)	-1.43*** (.22)	-1.39*** (.22)	-.52* (.13)	-.65*** (.13)	-.0.54*** (.15)	-.18 (.15)	-.84*** (.19)	-.24* (.11)	.21 (.21)	-.44** (.13)
.14 (.10)	.51 (.30)	.62* (.30)	.72* (.28)	.37* (.18)	.25 (.22)	.32 (.21)	.28 (.26)	.29 (.15)	-.33 (.30)	.25 (.19)
.23 (.13)	2.05*** (.42)	1.79*** (.42)	1.78*** (.39)	.33 (.26)	2.41*** (.30)	-.35 (.29)	1.37*** (.36)	-.10 (.21)	-.317*** (.41)	.77** (.26)
-.04 (.13)	.08 (.40)	.12 (.39)	.67 (.37)	.24 (.24)	.07 (.28)	.27 (.28)	.26 (.34)	.30 (.20)	.96* (.39)	.18 (.24)
.01 (.08)	.25 (.26)	.17 (.25)	.32 (.24)	.18 (.15)	.16 (.18)	-.14 (.18)	.10 (.22)	.02 (.13)	-.71** (.25)	-.01 (.16)
.04 (.07)	.88*** (.22)	.85*** (.22)	-.68*** (.21)	.44*** (.13)	-.39* (.16)	.07 (.15)	.53*** (.19)	.24* (.11)	.93*** (.22)	.08 (.14)
.14** (.05)	.26 (.15)	.25 (.15)	.60*** (.14)	.12 (.09)	.62*** (.11)	.19 (.11)	.15 (.13)	.13 (.08)	-.36* (.15)	.26** (.09)
-.05 (.05)	.04 (.14)	.04 (.14)	.16 (.16)	-.11 (.09)	.15 (.10)	.18 (.10)	.02 (.12)	.02 (.07)	.20 (.14)	.12 (.09)
.60 (.61)	-3.75 (.93)	-2.79 (.91)	-.18 (.178)	-.1.60 (.116)	-.1.71 (.137)	1.92 (.133)	-.2.94 (.1.66)	-.01 (.97)	2.73 (.1.88)	1.09 (.1.18)
.15 (.10)	1.10*** (.09)	1.15*** (.09)	.39* (.08)	.05 (.05)	.64*** (.06)	-.05 (.06)	.74*** (.07)	-.09* (.04)	-.82*** (.08)	.21*** (.05)
.68* (.23)	1.21 (.72)	1.32*** (.71)	4.32*** (.67)	1.40*** (.40)	2.22*** (.51)	1.92*** (.50)	1.92*** (.62)	.95*** (.36)	-1.80* (.71)	1.94*** (.44)
.43* (.21)	1.64* (.68)	1.52* (.67)	4.96*** (.63)	1.40*** (.41)	2.80*** (.49)	2.04*** (.47)	1.97*** (.59)	1.52*** (.34)	-2.50* (.67)	1.48** (.42)
-2.22** (.68)	-4.81** (.2.17)	-5.77*** (.2.15)	-5.52** (.2.29)	-3.07* (.1.31)	-3.08* (.1.55)	-5.19*** (.1.50)	-6.17*** (.1.87)	-4.37*** (.1.09)	-8.79*** (.2.12)	-5.31*** (.1.33)
-.50 (.78)	-3.60 (.2.48)	-4.16 (.2.45)	-6.00** (.2.29)	-.91 (.1.50)	-1.66 (.1.77)	-.99 (.1.71)	-2.53 (.2.13)	-.74 (.1.24)	-.14 (.2.42)	-.60 (.1.52)
-.20 (.21)	-.41 (.67)	-.2.6 (.67)	2.77*** (.52)	.47 (.41)	.97* (.48)	.83 (.47)	.61 (.58)	.14 (.34)	-2.08** (.66)	.83* (.41)
.21 (.16)	.29 (.51)	.51 (.50)	1.81*** (.47)	.31 (.31)	1.33*** (.36)	.67 (.35)	.65 (.44)	.27 (.36)	-1.59** (.50)	.81** (.31)
.18*** (.01)	.45*** (.04)	.44*** (.04)	1.5*** (.04)	.29*** (.02)	.02 (.03)	.08*** (.03)	.06 (.03)	-.08*** (.02)	1.12*** (.04)	.17*** (.02)
-.42*** (.01)	-.62*** (.04)	-.59*** (.04)	-1.00*** (.04)	-.60*** (.03)	-.48*** (.03)	-.64*** (.03)	-.43*** (.04)	-.28*** (.02)	1.19*** (.04)	-.60*** (.03)
.05*** (.01)	.03 (.02)	.03 (.02)	-.13*** (.02)	-.05*** (.01)	.22*** (.01)	.19*** (.01)	.16*** (.02)	.10*** (.01)	1.12*** (.04)	.09*** (.01)
.05*** (.01)	.12*** (.02)	.08*** (.02)	.32*** (.02)	.23*** (.01)	.05** (.02)	.07*** (.02)	-.0093 (.02)	.11*** (.02)	-.27*** (.02)	.09** (.01)
122.161	122.161	122.161	122.161	122.161	122.161	122.161	122.161	122.161	122.161	122.161
.02	.02	.02	.02	.02	.01	.01	.01	.01	.01	.01
81.54***	70.24***	66.96***	64.35***	63.96***	59.74***	53.90***	50.82***	47.84***	46.09***	37.32*

	unimprovable (43)	pestigions (44)	arrogant (45)	high quality (46)	best brand (47)
	.24*** (.02)	.06* (.03)	.15*** (.02)	-.52*** (.05)	-.13*** (.02)
	.02 (.05)	-.04 (.09)	.15* (.07)	.30* (.14)	-.10 (.06)
	-.34*** (.04)	-.50*** (.08)	-.61*** (.06)	-.37* (.14)	.26*** (.06)
	.23*** (.06)	.72*** (.11)	.17* (.08)	1.18*** (.18)	.25*** (.08)
	.01 (.04)	.56*** (.07)	.11 (.06)	.63*** (.12)	-.07 (.05)
	.17*** (.04)	.61*** (.07)	.25*** (.05)	.59*** (.11)	-.15*** (.05)
	-.27* (.13)	-.84*** (.24)	-.51*** (.18)	.04 (.39)	.49*** (.17)
	.28 (.17)	.61 (.32)	.49* (.24)	.38 (.52)	.05 (.22)
	.43*** (.10)	-.35 (.18)	1.06*** (.14)	-.78*** (.30)	-.69*** (.13)
	.23*** (.05)	.28** (.09)	.31*** (.07)	.42*** (.15)	.19*** (.06)
	-.09** (.03)	-.01 (.06)	-.07 (.05)	-.50*** (.10)	-.43*** (.04)
	-.19* (.09)	-.05 (.16)	.19 (.12)	-.23 (.26)	-.43*** (.11)
	-.03 (.12)	-.22 (.23)	-.12 (.17)	.16 (.36)	.32* (.16)
	-.30 (.17)	-.21*** (.31)	-.33 (.24)	-.195*** (.51)	.37 (.22)
	-.03 (.16)	.63* (.30)	-.21 (.22)	1.24** (.48)	.12 (.20)
	-.18 (.10)	-.41* (.19)	-.24 (.14)	-.37 (.31)	.15 (.13)
	.24** (.09)	.78*** (.17)	-.001 (.13)	.99*** (.27)	.29* (.11)
	-.06 (.06)	-.31** (.11)	-.01 (.09)	.03 (.18)	.11 (.08)
	.02 (.06)	.10 (.11)	.08 (.08)	.16 (.17)	.13 (.07)
	.67 (.76)	2.47 (.43)	1.18 (.09)	1.41 (.23)	-.63 (.99)
	-.08* (.03)	-.44*** (.06)	-.27*** (.05)	-.52*** (.10)	.29* (.04)
	-.01 (.29)	-.91 (.54)	.03 (.41)	1.13*** (.87)	1.37*** (.37)
	-.75* (.27)	-.178* (.59)	-.70 (.38)	1.29 (.82)	1.42** (.35)
	-.214* (.86)	4.97*** (1.61)	-.165 (.22)	-.1236*** (2.60)	-.286* (1.25)
	.66 (.98)	-.42 (.18)	-.03 (.39)	-.90 (2.97)	-.03 (.127)
	-.60* (.27)	-.136** (.50)	-.13 (.38)	-.107 (.81)	.22 (.35)
	-.22 (.20)	-.78* (.38)	-.23 (.29)	-.27 (.61)	.42 (.20)
	.17*** (.02)	.17*** (.03)	.03 (.02)	-.13** (.05)	-.09*** (.02)
	-.32*** (.02)	-.10** (.03)	-.23*** (.02)	-.28*** (.05)	-.24*** (.02)
	.11*** (.01)	.11*** (.01)	.22*** (.01)	.18*** (.02)	.06*** (.01)
	-.08*** (.01)	-.25*** (.02)	-.17*** (.01)	.02 (.03)	.14*** (.01)
	122.161	122.161	122.161	122.161	122.161
	.01	.01	.01	.01	.01
	33.38***	32.65***	31.70***	30.88***	27.31***

Note. \*  $p < .05$ ; \*\*  $p < .01$ ; \*\*\*  $p < .001$

Constant omitted from table. Sorted by R2. All VIFs below 5.