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Predicting the Personal Appeal of Marketing Images Using Computational Methods

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Images play a central role in digital marketing. They attract attention, trigger emotions, and shape consumers' first impressions of products and brands. We propose that the shift from one-to-many mass communication to highly personalized one-to-one communication requires an understanding of image appeal at a personal level. Instead of asking "How appealing is this image?" we ask "How appealing is this image to this particular consumer?" Using the well-established five-factor model of personality, we apply machine learning algorithms to predict an image's personality appeal—the personality of consumers to which the image appeals most—from a set of 89 automatically extracted image features (Study 1). We subsequently apply the same algorithm on new images to predict consequential outcomes from the fit between consumer and image personality. We show that image-person fit adds incremental predictive power over the images' general appeal when predicting (a) consumers' liking of new images (Study 2) and (b) consumers' attitudes and purchase intentions (Study 3).

Keywords Personalization; Digital advertising; Personality; Image appeal; Machine learning; Image processing; Computer vision

Images play a central role in digital communication and marketing. Not only do images outperform text in attracting attention (Pieters & Wedel, 2004), in triggering emotions (Lee, Amir, & Ariely, 2009), and in making advertisements more memorable (Childers & Houston, 1984), but they also play a crucial role in the formation of first impressions. Images are processed at a higher speed than text (Potter, Wyble, Hagmann, & McCourt, 2014), and consumers are likely to experience a cognitive and emotional response to the image in an advertisement before they read the accompanying text (Lindgaard, Fernandes, Dudek, & Brown, 2006). Although there are different ways of defining the success of images in the context of advertising (e.g., images can successfully capture attention by being surprising or even shocking; Messaris, 1997), most existing research on visual aesthetics is aimed at understanding and predicting image appeal (Palmer, Schloss, & Sammartino, 2013).

General Image Appeal

In line with the logic of traditional one-to-many mass communication, the majority of studies on visual aesthetics have focused on understanding and predicting the general appeal of images ("How appealing is this image to the average consumer?"). Research in the field of Empirical Aesthetics—a subdiscipline of Psychology—has linked visual appeal to various general aesthetic features, including colors and color combinations (Schloss & Palmer, 2011), levels of complexity and symmetry (Bauerly & Liu, 2008; Jacobsen & Hofel, 2002), perspective cues (Cerosaletti & Loui, 2009; Latto, Brain, & Kelly, 2000), and the presence or absence of people (Cerosaletti & Loui, 2009; Cyr, Head, Larios, & Pan, 2009). For example, people generally tend to prefer cold colors and high levels of saturation over warm

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colors and low levels of saturation (Palmer et al., 2013), and favor symmetrical compositions and low-to-intermediate image complexity (Bauerly & Liu, 2008; Jacobsen & Hofel, 2002). Building on this work, computer scientists have recently started to exploit the opportunities offered by advanced machine learning techniques to investigate image appeal at much larger scale and more fine-grained level of detail (Datta, Joshi, Li, & Wang, 2006). Some of the most frequently investigated features include the following: color and colorfulness, lighting conditions, complexity and simplicity, level of detail, size and aspect ratio, symmetry, sharpness, contrast, gist, texture, scene type, and salient objects. Although the field of Computational Aesthetics is relatively young, there is already a large body of empirical studies showing that computers can accurately predict the general aesthetic appeal of images on the basis of automatically extracted features (Ciesielski, Barile, & Trist, 2013; Datta et al., 2006; Dhar, Ordonez, & Berg, 2011; Khosla, Das Sarma, & Hamid, 2014; Machajdik & Hanbury, 2010; Murray, Marchesotti, & Perronnin, 2012; Redi & Povoa, 2013).

Personal Image Appeal

However, as digital marketing shifts from one-to-many communication that treats everyone the same to highly personalized communication (Shah, Rust, Parasuraman, Staelin, & Day, 2006; Sheth, Sisodia, & Sharma, 2000), there is a demand to predict image preferences on a deeper, personal level. In fact, while some images are generally more appealing than others, studies also show that people's preferences for certain image features are affected by demographic variables such as gender (Child, Hansen, & Hornbeck, 1968; Hurlbert & Ling, 2007; Palmer & Schloss, 2011) and age (Child et al., 1968). For example, preferences for saturated colors were found to be stronger in men than in women (Palmer & Schloss, 2011). While demographic variables hence provide a good starting point for examining individual differences in aesthetic preferences for photographic and artistic images, they very quickly reach their limits of discriminating between consumers in meaningful ways: It seems rather unrealistic to expect all women of a certain age to have the same aesthetic preferences.

Personal Image Appeal and the Five-Factor Model of Personality

In this article, we therefore go beyond the analysis of demographic variables and focus on psychological differences: their personality (McCrae & John, 1992). The five-factor model (McCrae & John, 1992) is the most widely established personality model and posits five personality traits: Openness (complex vs. conventional, uncreative), Conscientiousness (dependable, self-disciplined vs. disorganized, careless), Extroversion (outgoing, enthusiastic vs. reserved, quiet), Agreeableness (sympathetic, warm vs. critical, quarrelsome), and Neuroticism (calm, emotionally stable vs. anxious, easily stressed; Gosling, Rentfrow, & Swann, 2003). The five-factor model has not only been found to be stable across cultures (McCrae & Allik, 2002) as well as instruments and observers (McCrae & Costa, 1987) but it has also been linked to a broad variety of behaviors and preferences such as music preferences (Rentfrow & Gosling, 2003), vocational interests (Barrick, Mount, & Gupta, 2003), and political attitudes (Caprara & Zimbardo, 2004; for a comprehensive overview, see Ozer & Benet-Martínez, 2006).

Despite the general popularity of the five-factor model, there is little empirical evidence for the importance of personality in the context of image preference. The few existing studies to date have focused on personality-related preferences for painting styles (e.g., Chamorro-Premuzic, Reimers, Hsu, & Ahmetoglu, 2009; Furnham & Avison, 1997), abstract figures (e.g., Twomey, Burns, & Morris, 1998), individual colors (e.g., Birren, 1973; Robinson, 1975), and—most recently—user-generated pictures on Flickr (Cristani, Vinciarelli, Segalin, & Perina, 2013; Segalin, Perina, Cristani, & Vinciarelli, 2016). Segalin, Cheng, and Cristiani (2016), Segalin et al. (2016), for example, show that the personality trait of Extroversion is correlated with a preference for images with high contrasts in hue and saturation (textural properties) as well as images that showed people and faces (content).

Research Overview

In this article, we build on the methodology suggested by Segalin et al. (2016, 2016) to explore the importance of personality-based image preferences in the context of marketing visuals. In contrast to Segalin et al. (2016, 2016), we do not aim to predict the personality of a consumer, but the personality of an image. That is, we aim to predict how appealing an image is to different types of personalities. This shift from predicting consumer characteristics to predicting image characteristics offers new opportunities for personalized marketing. Knowing which personality traits an image appeals to the most means that marketers can selectively expose consumer segments of different personality profiles to those images that are most likely to elicit a positive response. We refer to this process as personality-matching. If a business, for example, decides to advertise to a segment of extroverted users, they can search their image database for those images that are predicted to have the highest Extroversion appeal. Hence, while our methodology builds on that of Segalin et al. (2016, 2016) we go beyond their findings by (a) predicting the personality appeal of an image instead of the personality of a user and by (b) illustrating the value of such predictions in the context of personality-matching.

To enable personality-matching in the context of personalizing visual advertising content, marketers need to be able to assess both the personality of their consumers and the personality of their potential marketing images. Furthermore, if personality-matching is to be implemented at scale, they need to be able to do so in an automated way. Recent research shows that instead of relying on self-report questionnaires, the personality of consumers can be predicted from their digital footprints such as the content of personal websites (Marcus, Machilek, & Schütz, 2006), Facebook or Twitter profiles (Kosinski, Stillwell, & Graepel, 2013; Youyou, Kosinski, & Stillwell, 2014), or language used in social media (Park et al., 2014; Schwartz et al., 2013; see Discussion for more details). In contrast, there is yet no automatic way of predicting the personality appeal of an image. Although companies can deploy focus groups and customer surveys to gauge the personality appeal of an image manually, such an approach suffers from two limitations. First, asking people to rate images manually is hardly scalable beyond a few hundred images. Second, the ratings might capture stereotypes of image appeal more than they capture actual personality-related preferences. In this article, we therefore suggest and evaluate a method to automatically predict the personality appeal of an image, and test whether consumers indeed prefer personality-matched images. As such, we aim to contribute to the existing literature not by providing deeper insights into the underlying mechanisms of personality-matching (compare, e.g., Lecky, 1945) but by providing a new practical approach to leveraging personality insights in applied marketing contexts. To support this contribution, we have made all code available on OSF (https://tinyurl.com/OSFmaterial; consult the “Feature Extraction and Predictive Modelling Guide” in Appendix S1 for guidance on how to use the materials).

Across three studies, we combine computer-based predictions with experimental paradigms. Study 1 tests whether we can use automated image feature extraction and machine learning techniques to predict (a) how appealing an image is to the average consumer (general appeal) as well as (b) how appealing an image is to consumer segments of specific personality traits (personality appeal). Studies 2 and 3 build on the insights of Study 1 to test whether considering the fit between the personality of a consumer and that of an image (image-person fit) allows us to predict individual-level image preferences with higher accuracy than using general image appeal alone. While study 2 predicts an individual’s liking of an image, Study 3 shows that personality appeal does not only predict a consumer’s immediate liking of an image but also spills over to their attitudes and purchase intentions toward brands that use such images in their marketing campaigns. Figure 1 outlines the methodological framework, highlighting the unique contributions of each study.

Study 1

In Study 1, we investigated whether automatically extracted image features can be used to accurately predict (a) an image’s general appeal as well as (b) an image’s personality appeal, defined as the personality of people to whom the image appeals most. While computational methods can easily turn into “black box” predictions that are difficult to understand and follow, we exclusively rely on feature extraction approaches and machine learning algorithms that allow for a certain level of interpretation.

Method

Image Selection

We selected 1,040 professional images from Shutterstock.com (a file with the corresponding Shutterstock image ids can be found in the OSF folder). The images were selected from 26 predefined categories that are suggested by Shutterstock (40 images per category) such as “Nature,” “Buildings,” and “People” (see Appendix S2 for a full list of categories).

Feature Extraction

We used computer algorithms to extract 89 features for each image, covering a wide spectrum of perceptual (i.e., content independent) and semantic

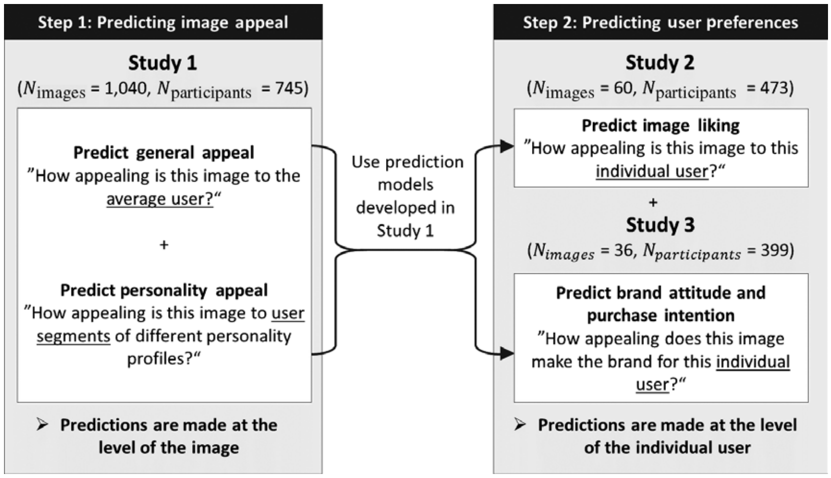

Figure 1. Overview and objectives of Studies 1–3.

(i.e., content dependent) aspects. Compared to more theory-driven approaches that thoroughly investigate the role of a specific image feature (e.g., gist: Pieters & Wedel, 2012; complexity: Pieters, Wedel, & Batra, 2010; color: Wedel & Pieters, 2014), we hence follow a more exploratory and practical approach that aims to take into account as much of the complexity captured in images as possible. While this approach does not allow us to deep-dive into the role of each specific feature and thoroughly investigate novel theoretical mechanisms, it enables us to maximize the predictive accuracy of general and personality-based image appeal. This approach is aligned with our research goal to provide a new practical approach to leveraging personality insights in applied marketing (rather than novel theoretical insights into the mechanisms of personality-based image appeal).

The selection of the 89 features follows the indication of Computational Aesthetics outlined in Introduction (Machajdik & Hanbury, 2010; Segalin et al., 2016) and has been extended in order to take into account more content information. While there is an almost unlimited range of features one can extract from images, this selection constitutes a comprehensive set of the most important features as discussed in previous work on the topic (Segalin et al., 2016, 2016). The features can be split into four main categories: color, composition, textural properties, and content. Table 1 provides an overview of all features alongside the citations of original articles introducing the methods to extract those features. Details on how the methods were developed would go beyond the scope of this article. However, interested readers can find the description of how features were extracted in the cited references, and we have made all code available on OSF.

Color is represented by the HSV model, measuring hue, saturation, and value (the latter is often referred to as brightness). Color features include distributions of colors (e.g., average, standard deviation and variance of hue, saturation, and value), predicted emotions elicited by the colors (in terms of valence, arousal, and dominance), color diversity, and the proportion of different colors from a set of 11 standard colors (e.g., red, yellow, blue).

Composition refers to the spatial organization of visual elements in an image, independent of the image's subject. Composition features account for density of edges, number and average size of visually homogeneous regions (i.e., regions with similar characteristics), application of common composition techniques (rule of thirds and blurring of background), size, and aspect ratio of the picture.

Texture refers to the spatial arrangement of intensity and colors in an image or in an image region. Textural features capture perceptual aspects (e.g., their statistical properties are different in sharp and blurred pictures) and provide implicit information about the subject of an image (e.g., textures tend to be more regular in pictures showing artificial objects than in pictures showing natural landscapes). In addition, textural features account for image granularity, contrast, coarseness, directionality, and homogeneity.

Content refers to the objects in an image. Although the list of potential objects is almost unlimited, the literature proposes several approaches aimed at finding objects that appear more frequently than others (Felzenszwalb, Girshick, McAllester, & Ramanan, 2010). In this work, we examine

Table 1
Feature Synopsis

Name	N	Short description
Color		
Hue, saturation, and value (HSV) statistics	5	Average saturation, standard deviations of saturation and value (Machajdik & Hanbury, 2010); circular variance in HSV color space (Mardia & Jupp, 2000); use of light as the average pixel intensity of value channel (Datta et al., 2006)
Emotion-based	3	Measurement of predicted valence, arousal, dominance (Machajdik & Hanbury, 2010; Valdez & Mehrabian, 1994)
Color diversity	1	Distance with regard to a uniform color histogram, by earth mover's distance (EMD; Datta et al., 2006; Machajdik & Hanbury, 2010).
Color name	11	Amount of black, blue, brown, green, gray, orange, pink, purple, red, white, yellow (Machajdik & Hanbury, 2010)
Composition		
Edge pixels	1	Total number of edge points, extracted with Canny detector (Lovato et al., 2014)
Level of detail	1	Number of regions after mean shift segmentation (Christoudias, Georgescu, & Meer, 2002; Comaniciu & Meer, 2002)
Average region size	1	Average size of the regions after mean shift segmentation (Christoudias et al., 2002; Comaniciu & Meer, 2002)
Low depth of field (DOF)	3	Amount of focus sharpness in the inner part of the image w.r.t. the overall focus (Datta et al., 2006; Machajdik & Hanbury, 2010)
Rule of thirds	2	Average of saturation and value channels in the inner rectangle of the image (Datta et al., 2006; Machajdik & Hanbury, 2010)
Image properties	2	Size aspect ratio of the image (Datta et al., 2006; Lovato et al., 2014)
Texture		
Gray distribution	1	Image entropy (Lovato et al., 2014)
Wavelet-based textures	12	Level of spatial graininess measured with a three-level (L1, L2, and L3) Daubechies wavelet transformation on the HSV channels (Datta et al., 2006)
Tamura	3	Amount of coarseness, contrast, directionality (Tamura, Mori, & Yamawaki, 1978)
GLCM features	12	Amount of contrast, correlation, energy, homogeneity for each HSV channel (Machajdik & Hanbury, 2010)
GIST descriptors	1	Output of GIST filters for scene recognition that produce an original set of 24 features, including the naturalness, openness, roughness, expansion, and ruggedness (Oliva & Torralba, 2001). For the sake of parsimony, we averaged the 24 GIST filters to form a single GIST predictor
Content		
Object detectors	18	The number of instances (#) and their average bounding box size for nine popular objects: person, airplane, bicycle, bottle, bus, car, cat, motorbike, and chair (Felzenszwalb et al., 2010)
Faces	3	Number of faces, area of bounding boxes, and pose angle (Viola & Jones, 2001)
Upper bodies	1	Area of bounding box of upper-body detector for frontal viewpoint (Ferrari, Marin-Jimenez, & Zisserman, 2008)
Number of people	1	Manually annotated number of people present in the image with three levels (none, one person, several people)
Visual clutter	2	Feature congestion and measures to describe the busyness of an image (Rosenholtz, Li, Mansfield, & Jin, 2005)
Computer Graphics	5	192 geometrical features to distinguish between computer graphics and natural images that were aggregated to five predictors describing intensity surface gradient, Beltrami flow feature, second fundamental form, color patch, grayscale patch (Ng & Chang, 2004; Ng, Chang, Hsu, Xie, & Tsui, 2005)

Note. N = number of features used in the analysis.

nine popular objects (e.g., cats or people). As people are one of the most frequent subjects of images and are known to influence aesthetic preferences (Cerosaletti & Loui, 2009; Cyr et al., 2009), we additionally extracted features related to the presence of people such as faces and upper bodies. We also obtained manual annotations of the number of people in every image by surveying workers on Amazon Mechanical Turk. The set of content features is completed by computer graphics features that allow us to distinguish between natural and artificial images. While we hence include content as a dimension in our feature selection spectrum, readers should be aware that importance of content features in the prediction of image appeal might be underestimated due to the restriction in the breadth of features (see General Discussion for more details on how this could be overcome by deep learning methods in approaches that exclusively focus on prediction rather than interpretable findings).

Figure 2 displays a number of image pairs that illustrate the nature of some of the image features outlined earlier. As the examples illustrate, there was a broad variety of images that translated into a good range of image features across the four categories.

We recognize that the selected features represent a noncomprehensive assortment of possible image features. In fact, the application of deep learning-powered image recognition methods, which automatically extract patterns on pixel level, might have allowed us to capture more nuanced aspects of image appeal. However, while powerful, the patterns extracted from deep learning algorithms are often a black box to the researcher and almost impossible to interpret. As the goal of this article was not to maximize the predictive accuracy of our models, but to provide an understanding of which aspects of an image make it more or less appealing to different types of personalities, we decided to focus on the predefined features outlined earlier (see Discussion for future research directions using more alternative computer vision techniques).

Participants and Procedure

We recruited 745 participants on Amazon Mechanical Turk. The desired sample size (N = 800) was determined such that each image would be rated by 40 participants. Given that we had to exclude a number of participants retrospectively, the final sample size was N = 745. The average age was 35.4 years (SD = 10.6), and 48% of participants

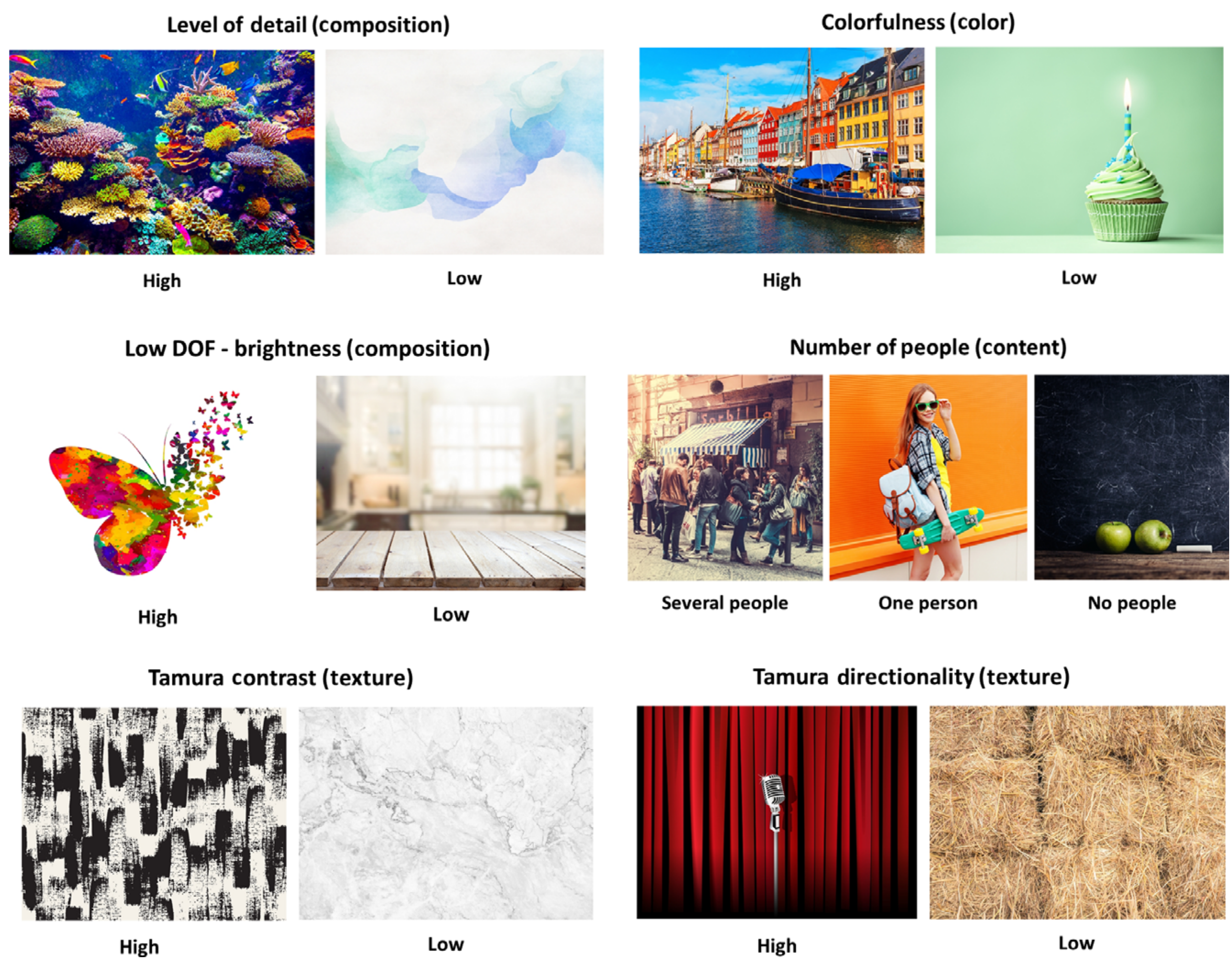

Figure 2. Visual illustration of six of the image features.

indicated to be female. Each participant was presented with a subset of 52 images (two images randomly selected from each of our Shutterstock categories; see Appendix S2). In a first step, participants were asked to rate each of the images according to how much they liked the image ("How much do you like this image?") using a 7-point Likert scale ranging from 1 = not at all to 7 = extremely. This resulted in a total number of 38,740 ratings. In a second step, participants were asked to complete the 50-item IPIP (Goldberg et al., 2006), a widely used measure of the five-factor model of personality.

Calculation of Image Appeal

We calculated the general appeal of images in two steps. Because each participant only rated a subset of images, we first z-standardized preference ratings within participants. We subsequently averaged all the ratings for each image to form a general image appeal variable.

To identify how appealing an image is to people scoring high or low on each of the five personality traits, we calculated five personality scores for each image using two components: (a) participants' preference ratings and (b) participants' personality scores. In order to be able to combine the two components in a meaningful way, we first *z*-standardized preference ratings (within participants) and *z*-standardized personality scores (across participants). Preference ratings therefore indicate how much a person *p* likes an image *i* in comparison with the other images they rated: As the average rating for each person is now zero, all images that a person likes more than average are associated with a positive value ($z_p(Rating_{\mathrm{i}}) > 0$) and all images that the person likes less than average are associated with a negative value ($z_p(Rating_{\mathrm{i}}) < 0$). Personality scores were standardized across participants and therefore reflect the personality of a person in relation to the reference sample. A positive Extroversion score ($z(Extroversion_{\mathrm{p}}) > 0$), for example, indicates that a person is more extroverted than the average person in our sample, while a negative Extroversion score ($z(Extroversion_{\mathrm{p}}) < 0$) suggests that the person is less extroverted than the average person in our sample. Based on the z-standardized preference ratings and personality scores, we calculated an image's personality appeal in three steps (demonstrated for the Extroversion trait): First, for each image *i* we identified the subsample of participants n_i who had rated the image. Second, we multiplied the person-standardized image rating $z_p(Rating_{\mathrm{i}})$ and the sample standardized personality score $z(Extroversion_{\mathrm{p}})$ of each person in n_i. Given that both preference ratings and personality scores were centered around zero, this procedure results in participant-specific image scores (e.g., participant-specific image Extroversion appeal EA_{pi}) that have the following characteristics:

1. An image will receive a positive participant-specific Extroversion score (EA_{pi}) if it is liked ($z_p(Rating_{\mathrm{i}}) > 0$) by an extrovert ($z(Extroversion_{\mathrm{p}}) > 0$) or if it is disliked ($z_p(Rating_{\mathrm{i}}) < 0$) by an introvert ($z(Extroversion_{\mathrm{p}}) < 0$).
2. An image will receive a negative participant-specific Extroversion score (EA_{pi}) if it is liked ($z_p(Rating_{\mathrm{i}}) > 0$) by an introvert ($z(Extroversion_{\mathrm{p}}) < 0$) or if it is disliked ($z_p(Rating_{\mathrm{i}}) < 0$) by an extrovert ($z(Extroversion_{\mathrm{p}}) > 0$).
3. An image will receive a neutral (close to zero) participant-specific Extroversion score (EA_{pi}) if the participant's preference rating or personality score is average (close to zero).

Third, we averaged the resulting scores across all participants in n_i. Similar to step 2, this procedure results in overall image scores (e.g., general Extroversion score EA_i) with the following characteristics:

1. An image will receive a highly positive overall Extroversion score (EA_i) if it is liked by the majority of extroverts and disliked by the majority of introverts.
2. An image will receive a highly negative overall Extroversion score (EA_i) if it is liked by the majority of introverts and disliked by the majority of extroverts.
3. An image will receive a neutral overall Extroversion score (EA_i) close to zero if (a) introverts and extroverts do not have a strong positive or negative preference for the image or (b) the preferences of introverts and extroverts go in the same direction (e.g., all participants like the image).

Equation 1 describes how we calculated the Extroversion appeal score (EA_i) for an image *i*, summarizing the steps above:

$$EA_i = \frac{\sum_{p=1}^{n_i} C_p(Rating) \times z(Extroversion_p)}{n_i} \qquad (1)$$

Following the outlined example for the personality trait of Extroversion, we calculated the personality appeal for all the Big Five personality traits. In contrast to other measures of product or brand personality which aim at assessing the perceived or attributed characteristics of the product (Aaker, 1997), our measure of an image's personality appeal therefore reflects the personality of the people who liked or disliked the image.

Results

Prediction Models

We used machine learning techniques to predict the general and personality appeal of an image from its full set of visual features. It would have been desirable to not only look at image features in isolation, but take into account their interactions (e.g., the combined effect of high saturation and low level of detail). However, even focusing only on two-way interactions results in an additional 3,916 predictors in the model. Given the fact that we only had a limited number of images (N_{images} = 1,040) to train the model on, we did not include the interaction terms in our analysis.

Given the relatively small set of observations (N_{images} = 1,040), we also simplified the prediction task to a classification task by dichotomizing the general and personality appeal scores. Turning continuous into categorical outcome data is common practice in the computer science literature (e.g., de Montjoye, Quoidbach, Robic, & Pentland, 2013; Segalin et al., 2016, 2016) and—similar to extreme group comparisons in experimental setups—serves the purpose of reducing the complexity of the prediction task by maximizing between-group differences. All scores above the mean were assigned a score of 1, while all scores below the mean were assigned a score of 0. For each of the five personality traits as well as the general appeal scores, we performed sparse regression analyses using binomial LASSO models (Tibshirani, 1996; see Appendix S3 for a technical description of LASSO models). We decided to favor LASSO regression over other machine learning models such as support vector machine (Hearst, Dumais, Osuna, Platt, & Scholkopf, 1998) or random forest models (Liaw & Wiener, 2002) as they allow for an interpretation of coefficients similar to those of a standard regression analysis. In line with our decision to study concrete features rather than applying deep learning algorithms, the focus on LASSO models was guided by our desire to avoid a "black box" approach. Because LASSO models perform both variable selection and regularization at the same time, they are particularly suited for situations in which there are a large number of potentially correlated predictors. The classification tasks were performed using an averaged hold-out protocol in which the classifier is trained over 90% of the dataset and tested out-of-sample on the remaining 10%. Instead of randomly dividing the sample in 90% training and 10% testing subsamples, this procedure produces a balanced number of response categories in both training and testing samples. For each trait, we fine-tuned the LASSO parameter t over a set of values ranging between -20 and 20. This procedure is repeated 10 times with shuffled training/testing partitions. For each iteration, we computed two performance indicators that compare actual and predicted appeal scores for each of the five personality appeal scores: (a) the Spearman correlation and (b) the percentage of accurately classified images (classification accuracy against a baseline of 50%). Both indicators were subsequently averaged across the 10 repetitions to form overall indicators of accuracy. The results are displayed in Table 2. Taken together, the prediction accuracies were found to be highest for Extroversion and Neuroticism, closely followed by Openness, Agreeableness, and Conscientiousness.

Correlational Analyses

To provide a better understanding of the prediction results, this section reports bivariate relationships between the 89 image features and (a) the general image appeal as well as (b) the five personality-specific appeal scores. Following the recommendations of De Winter, Gosling, and Potter (2016), we use Spearman instead of Pearson correlations to avoid biases arising from heavy-tailed distributions or outliers. Figure 3 illustrates the correlations visually, with red background colors indicating negative correlations and green indicating positive correlations.

General appeal was highly positively correlated with the average saturation, the predicted dominance and arousal, saturation and brightness wavelets, GIST, and the level of detail. In contrast, the general appeal of an image was negatively related to the use of light, the color white, Tamura directionality (which is the degree to which the image is defined by clear lines indicating directionality), saturation/brightness energy, and homogeneity as well as the number of people (this is only a selection of the strongest correlations, please see Figure 3 for a more detailed overview of all correlated features). This pattern suggests that people generally prefer stimulating images, which are highly saturated and associated with emotions such as

Table 2
Results of LASSO Regressions in Terms of Average Spearman Correlations and Classification Accuracies over 10 Repetitions (Including SDs in Brackets)

	General	O	C	E	A	N
Spearman ρ	0.61 (0.08)	0.36 (0.08)	0.29 (0.08)	0.44 (0.07)	0.32 (0.09)	0.41 (0.09)
Classification accuracy	68% (4%)	67% (4%)	65% (4%)	72% (4%)	66% (4%)	69% (4%)

Note. A = Agreeableness; C = Conscientiousness; E = Extroversion; N = Neuroticism; O = Openness.

dominance and arousal. The positive correlation with GIST in addition to the negative correlation with the number of people further suggests that people generally favor natural scenes containing few or no people over artificial scenes featuring several people.

Openness appeal was positively correlated with the colors blue and black, as well as brightness wavelets. In contrast, Openness appeal was negatively correlated with the colors brown, orange, and pink, as well as several people-related features such as area of body and the number of people. This pattern suggests that open-minded people favor images with no people and images with rather cold colors over images with warm colors and images that feature people and faces. In line with the general link between Openness and art (McCrae & Greenberg, 2014; McCrae & John, 1992) as well as more specific relationships between Openness and the preference for abstract art (Feist & Brady, 2004), the correlations of Openness and people-related features might partly be explained by the fact that abstract photography or artistic paintings normally do not feature people (or would not be classified as such). Openness is known to be related to IQ, divergent thinking, and creativity (McCrae & Greenberg, 2014). Therefore, the correlations between Openness and the preferences for the colors black and blue might be driven by the fact that in our set of images those colors were associated with images in the categories Technology and Science.

Conscientiousness appeal was positively correlated with color valance, the color red, the rule of thirds, Tamura coarseness, and the predicted presence of at least one person (area box person). In contrast, Conscientiousness appeal was negatively correlated with the color black and aggregated GIST descriptors. This pattern suggests that highly conscientious people prefer images that capture their attention with positive and warm colors and wider textures, such as wide and homogeneous backgrounds or buildings with windows. The negative correlation with GIST additionally proposes that highly conscientious people favor non-natural images.

Extroversion appeal was positively correlated with the color pink, the average size of image regions, low hue, saturation, value (brightness), depth of field (DOF, which is the amount of focus sharpness in the inner part of the image compared to the overall focus), Tamura coarseness and directionality, various GLCM features (which refer to the amount of contrast, correlation, energy, homogeneity for each HSV channel), and people-related features such as person and body area boxes, face pose angle, the number of people, and computer graphic features. In contrast, Extroversion appeal was negatively correlated with the level of detail and edges, wavelet and GLCM contrast features related to saturation and hue, GIST, and busyness of the image. This pattern suggests that extroverted people prefer simple images and images that feature people. The correlations with low DOF, busyness, and GIST suggest that this preference could be particularly pronounced for portraits. The links between Extroversion and people-related features are in line with extroverts' general tendency to favor social situations and the company of other people (McCrae & John, 1992). The correlations with computer graphics features, Tamura, GLCM, and busyness further suggest that extroverts might favor non-natural, processed ("photoshopped") images. A potential explanation for this relationship is that extroverts attach greater importance to how one looks (Kvalem, von Soest, Roald, & Skolleborg, 2006) and therefore are more attracted to the flawless nature of processed images.

Agreeableness appeal was positively correlated with the use of light, color valence, the presence of the colors brown, green, pink, purple, red, and yellow, GLCM correlation, Tamura coarseness, face pose angle, the number of people, and computer graphic features. In contrast, Agreeableness was negatively correlated with the color black, brightness wavelets, and GIST. This pattern suggests that highly agreeable people prefer images with warm colors and images with people. The outlined

Colors

General	O	C	E	A	N	Feature
-0.13	-0.05	0.05	0.01	0.06	0.04	Use of light
0.23	0.00	0.01	-0.04	0.00	-0.02	Saturation (mean)
0.09	0.01	-0.01	0.01	0.00	-0.02	Saturation (sd)
0.05	0.04	-0.04	0.02	-0.03	-0.04	Brightness (sd)
-0.05	-0.05	0.06	-0.01	0.07	0.03	Valence
0.18	0.04	-0.04	-0.02	-0.06	-0.04	Dominance
0.23	0.01	-0.01	-0.03	-0.03	-0.04	Arousal
0.03	-0.01	-0.04	0.05	0.03	0.03	Hue circular variance
-0.08	-0.04	0.02	-0.04	-0.03	-0.01	Colorfulness
-0.01	0.06	-0.08	0.02	-0.07	-0.04	Black
0.07	0.06	-0.03	0.01	0.00	0.00	Blue
0.06	-0.07	0.03	0.04	0.06	-0.07	Brown
-0.06	0.02	-0.03	0.05	-0.01	-0.01	Gray
0.20	-0.02	0.03	0.00	**0.10**	-0.02	Green
0.11	-0.07	0.01	0.01	0.05	-0.03	Orange
-0.07	-0.07	0.04	**0.11**	**0.10**	0.03	Pink
0.06	0.00	0.01	0.06	0.08	-0.01	Purple
0.05	-0.03	0.06	0.05	**0.10**	-0.01	Red
-0.23	-0.03	0.00	0.04	0.03	0.04	White
0.22	-0.04	0.05	-0.03	0.07	-0.02	Yellow

Texture

General	O	C	E	A	N	Feature
0.18	0.03	-0.04	-0.04	0.00	0.03	Gray distribution Entropy
-0.01	0.00	-0.05	0.05	0.00	0.02	Hue wavelet (Level 1)
0.01	0.00	-0.05	0.04	0.01	0.03	Hue wavelet (Level 2)
0.01	0.00	-0.04	0.04	0.01	0.03	Hue wavelet (Level 3)
0.26	0.05	-0.05	-0.07	-0.04	0.00	Saturation wavelet (Level 1)
0.22	0.05	-0.05	-0.07	-0.04	0.02	Saturation wavelet (Level 2)
0.14	0.03	-0.06	-0.06	-0.02	0.03	Saturation wavelet (Level 3)
0.25	0.06	-0.04	**-0.11**	-0.06	0.05	Brightness wavelet (Level 1)
0.19	0.06	-0.05	**-0.10**	-0.06	0.05	Brightness wavelet (Level 2)
0.12	0.06	-0.05	-0.07	-0.06	0.03	Brightness wavelet (Level 3)
0.01	0.00	-0.04	0.04	0.01	0.03	Hue wavelet (mean)
0.18	0.04	-0.06	-0.07	-0.03	0.02	Saturation wavelet (mean)
0.16	0.06	-0.05	**-0.09**	-0.06	0.04	Brightness wavelet (mean)
-0.06	-0.02	0.07	**0.15**	**0.10**	**-0.10**	Tamura coarseness
0.00	0.05	-0.02	0.05	0.01	-0.04	Tamura contrast
-0.25	-0.06	0.02	**0.10**	0.02	-0.04	Tamura directionality
-0.01	-0.01	-0.03	0.05	0.02	0.00	Hue contrast (GLCM)
0.02	-0.03	0.03	0.05	0.08	-0.01	Hue correlation (GLCM)
-0.09	-0.03	0.01	-0.05	-0.07	-0.01	Hue energy (GLCM)
-0.02	-0.03	0.06	-0.02	0.01	-0.02	Hue homogeneity (GLCM)
0.20	0.06	-0.05	-0.07	-0.03	0.01	Saturation contrast (GLCM)
-0.13	-0.05	0.05	**0.10**	0.08	-0.03	Saturation correlation (GLCM)
-0.22	0.01	0.00	0.00	0.00	0.03	Saturation energy (GLCM)
-0.27	-0.03	0.04	0.06	0.03	0.00	Saturation homogeneity (GLCM)
0.18	0.06	-0.04	-0.09	-0.06	0.03	Brightness contrast (GLCM)
-0.13	-0.04	0.03	**0.16**	0.07	-0.09	Brightness correlation (GLCM)
-0.21	-0.05	0.02	0.01	-0.01	0.01	Brightness energy (GLCM)
-0.25	-0.05	0.04	0.09	0.03	-0.04	Brightness homogeneity (GLCM)
0.24	0.05	-0.06	**-0.13**	-0.08	0.06	GIST

Composition

General	O	C	E	A	N	Feature
0.24	0.02	-0.04	**-0.09**	-0.03	0.06	Number of edge points
0.26	0.04	-0.04	-0.07	0.01	0.04	Level of detail
-0.26	-0.04	0.04	0.07	-0.01	-0.04	Region size (mean)
-0.03	0.00	0.00	0.04	0.05	-0.04	Low DOF - Hue
-0.07	-0.02	0.03	0.06	0.04	-0.06	Low DOF - Saturation
-0.08	-0.01	0.01	0.07	0.02	-0.01	Low DOF - Brightness
0.18	-0.01	0.00	-0.01	0.00	-0.03	Rule of thirds - Saturation
-0.10	-0.02	0.08	0.00	0.06	0.01	Rule of thirds - Brightness
-0.05	0.02	-0.01	-0.01	0.03	0.06	Image size
-0.04	0.01	0.00	-0.01	0.03	0.06	Aspect ratio

Content

General	O	C	E	A	N	Feature
-0.15	-0.05	0.00	0.04	-0.02	0.00	Number of people
-0.13	-0.07	0.07	0.07	0.04	-0.01	Region of people
0.08	-0.02	0.03	0.05	0.04	0.02	Number of airplanes
0.08	-0.02	0.03	0.05	0.04	0.02	Region of airplanes
-0.01	-0.05	0.01	-0.03	0.04	0.00	Number of bicycles
-0.01	-0.05	0.01	-0.03	0.04	0.00	Region of bicycles
0.01	-0.06	0.05	-0.02	-0.03	0.04	Number of bottles
0.01	-0.06	0.05	-0.02	-0.03	0.04	Region of bottles
0.05	0.05	0.00	-0.01	0.02	0.00	Number of busses
0.05	0.05	0.00	-0.01	0.02	0.00	Regions of busses
-0.03	0.03	-0.01	0.00	0.01	0.04	Number of cars
-0.03	0.03	-0.01	0.00	0.01	0.04	Region of cars
0.01	0.00	-0.04	0.01	-0.04	0.06	Number of cats
0.01	0.00	-0.04	0.01	-0.04	0.06	Region of cats
0.04	0.03	0.01	0.03	0.03	-0.03	Number of motorbikes
0.04	0.03	0.01	0.03	0.03	-0.03	Region of motorbikes
-0.04	-0.02	0.02	0.02	0.03	0.00	Number of chairs
-0.04	-0.02	0.02	0.02	0.03	0.00	Region of chairs
-0.05	0.06	0.01	0.03	0.02	-0.02	Number of faces
-0.09	-0.08	-0.02	**0.11**	0.07	-0.07	Angle of face
-0.05	0.06	0.01	0.03	0.02	-0.02	Region of faces
-0.11	-0.08	0.02	**0.08**	0.04	**-0.10**	Region of bodies
0.05	0.04	-0.03	-0.07	-0.05	0.05	Congestion clutter
0.14	0.04	-0.03	-0.07	-0.02	0.05	Subband entropy clutter
-0.16	-0.03	0.05	**0.10**	0.07	-0.05	CS - intensity surface gradient
-0.18	-0.02	0.05	**0.12**	0.05	-0.07	CS - betrami flow feature
-0.21	-0.02	0.05	**0.13**	0.05	-0.08	CS - second fundamental form
-0.09	-0.05	0.02	0.06	0.02	-0.03	CS - color patch
-0.05	-0.03	0.01	-0.01	-0.06	-0.03	CS - grayscale patch
-0.20	-0.07	0.04	**0.23**	**0.13**	**-0.15**	Number of people (manual)

Figure 3. Spearman correlations between the 89 features and general appeal as well as personality appeal scores. Correlations highlighted on black background were positively significant at α = .05, and all correlations circled with a black frame were negatively significant at α = .05. All correlations marked in bold were significant after applying a Benjamini–Hochberg (FDR) correction for multiple comparisons (Benjamini & Hochberg, 1995).

relationships are in accordance with the general description of the Agreeableness trait which characterizes agreeable people as warm and caring and highlights their preference for close and harmonious relationships with other people (McCrae & John, 1992).

Neuroticism appeal was positively correlated with image size and aspect ratio, GIST, and the display of cats. In contrast, Neuroticism appeal was negatively correlated with the color brown, Tamura coarseness, and the presence of people and faces. This pattern suggests that people high in Neuroticism prefer natural images and images with no people. This preference for calm and minimally stimulating scenes without people is in line with the general attributes of Neuroticism, including envy, loneliness, anxiety, and fear (McCrae & John, 1992). Given that the personality traits of Extroversion and Neuroticism are negatively correlated ($r = -.42$ in our sample), it is not surprising that the patterns found for Neuroticism are inverse to those reported for Extroversion.

The results of Study 1 show that the extent to which an image of certain characteristics appeals to a particular consumer segment partly depends on the personality profile of that segment, and that machine learning algorithms can be used to automatically predict the personality appeal of an image from automatically extracted image features. The findings of Study 1 provide support for the importance of individual differences in understanding image appeal.

Study 2

Study 2 used the models developed in Study 1 to demonstrate the added value of predicting an image's personality appeal in addition to its general appeal. We tested whether the fit between the self-reported personality profile of a participant and the personal appeal of a new set of images could be used to predict the participant's attitude toward these images above and beyond their general appeal.

Method

Image Selection and Personality Predictions

We selected a total of 60 images in the three product categories "holiday," "beauty," and "phone" (20 images per product category) from Shutterstock.com and extracted the same low-level features as in Study 1 (see Table 1). We chose these categories because they reflect neutral products that should equally appeal to consumers of different types of personality profiles (e.g., most people own a mobile phone and most people are interested in going on holidays, regardless of their personality). Using the LASSO models developed in Study 1, we predicted the images' (a) general appeal as well as the (b) personality appeal for the five personality traits.

Assessment of Preference Ratings

Participants were randomly assigned to one of the image categories. Image preferences were assessed using a comparative judgment format with pairwise comparisons of images (Bradley & Terry, 1952; Palmer et al., 2013). Instead of making absolute preference judgments ("How much do you like this image"), participants indicated which of two simultaneously presented images they preferred aesthetically ("Which image do you like better?"). Given that comparative judgment tasks do not require any memory load, they do not only make ratings easier for consumers but they also result in higher consistencies across ratings and therefore higher overall data quality (Palmer et al., 2013). By observing several such comparisons, it is subsequently possible to build a measurement scale that produces absolute values and no longer depends on pairwise comparisons which are often more difficult to analyze (Bradley & Terry, 1952). Following the logic of comparative judgment tasks, we presented two images to participants at a time. The comparative judgment task was completed on the website nomoremarking.com. Figure 4 illustrates an example comparison. The position of images (right or left) and order of comparisons were randomized. Participants were asked "Which image do you like better?" As each of the 20 images was compared to all other images, participants had to make a total number of 190 judgments. In order to calculate consumers' absolute preference rating for each of the 20 images, we estimated a Bradley–Terry model (Bradley & Terry, 1952) using the "BradleyTerry2" package in R (Turner & Firth, 2012).

Participants and Procedure

We recruited participants through University mailing lists and Facebook groups in the United Kingdom and Germany. Given that we expected the effects to be small, we aimed to recruit 400+ students. Participants were randomly assigned to the "holiday," "beauty," or "phone" condition. Because the pictures from shutterstock.com all feature female models, the condition "beauty" was only assigned to female participants. This was done to prevent unintended effects arising from preferences for the same/opposite sex. Participants were

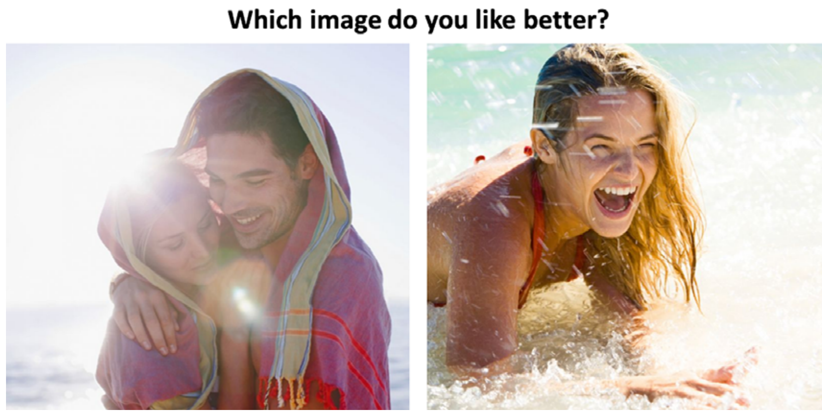

Figure 4. Example of a comparative judgment trial in the "holiday" condition.

not paid, but they received feedback about their personality scores at the end of the study (see Kosinski, Matz, Gosling, Popov, & Stillwell, 2015). In a first step, participants were asked to complete the 50-item IPIP (Goldberg et al., 2006). We used back-translated items for German-speaking participants. In a second step, participants were asked to complete the comparative judgment task outlined previously. In order to maintain high data quality, we did not force participants to respond to all personality questions or comparative judgment ratings. However, we only included participants in the analysis if they (a) had responded to more than 40% of the IPIP items (corresponding to four items per trait as used in short measures such as the TIPI, Gosling et al., 2003) and (b) completed all of the 190 comparative judgment tasks. The final sample therefore consisted of 468 participants. Of the participants who provided demographic information, 61% indicated to be female. The average age was 22.5 years (*SD* = 4.4).

Calculation of Participant-Image Fit

We calculated the fit between participants' self-reported personality profiles and the personality appeal of the images they rated (IP-fit) using an established fit measure (see, e.g., Matz, Gladstone, & Stillwell, 2016). Based on the sample z-standardized personality scores of participants and images, the measure first estimates the Euclidean distance between the personality profiles of a person p and that of an image i across all the five personality traits (Deza & Deza, 2009). To facilitate the interpretation of results, the distance estimate is subsequently subtracted from the mean so that higher values indicate a better fit. Equation 2 describes the calculation of image-person fit:

$$IP-fit_{p,i} = \text{mean} - \sqrt{\left(z\left(O_p\right)-z(O_i)\right)^2+\cdots+\left(\left(z\left(N_p\right)-z(N_i)\right)^2\right)} \tag{2}$$

Prediction Models

Given that there were multiple observations per participant, we used multilevel modeling with the image-person fit (IP-fit) nested in participants (allowing for random intercepts). Model 1 includes the predicted general appeal as a sole predictor of the image preference rating. Model 2 adds the IP-fit variable to establish its incremental value above and beyond general appeal. Finally, Model 3 controls for participants' age and gender as well as the main effects of participant and image personalities as additional control variables. Due to the high intercorrelation between the predicted image personalities for Extroversion and Neuroticism ($r = -.99$), we omitted the main effect of image Neuroticism to avoid estimation problems stemming from multicollinearity (Gujarati & Porter, 2009).

Results

As the results in Table 3 show, general appeal was a highly significant predictor of participants' preference ratings (Model 1, see Appendix S4 for the univariate correlations between variables). The fit between the personality appeal of an image and the self-reported personality of a participant (IP-fit) was found to significantly predict preference ratings alongside of general appeal (Model 2). Although the predictive power of IP-fit is only about half as

Table 3
Multilevel Models Predicting Preference Rating

Predictors	Model 1			Model 2			Model 3		
	b	*SE*	*t*	*b*	*SE*	*t*	*b*	*SE*	*t*
Gen. appeal	0.39***	0.026	14.71	0.42***	0.027	15.66	1.05***	0.22	4.72
IP-fit	–	–	–	0.19***	0.025	7.83	0.021***	0.032	6.59
Gender	–	–	–	–	–	–	−0.056	0.059	−0.97
Age	–	–	–	–	–	–	−0.003	0.007	−0.40
Person-O	–	–	–	–	–	–	−0.034	0.029	−1.19
Person-C	–	–	–	–	–	–	0.001	0.027	0.029
Person-E	–	–	–	–	–	–	0.007	0.029	0.24
Person-A	–	–	–	–	–	–	−0.001	0.031	−0.018
Person-N	–	–	–	–	–	–	−0.007	0.029	−0.247
Extremity	–	–	–	–	–	–	0.37***	0.10	3.69
Image-O	–	–	–	–	–	–	0.54*	0.25	2.18
Image-C	–	–	–	–	–	–	0.42***	0.044	9.43
Image-E	–	–	–	–	–	–	0.55***	0.033	15.74
Image-A	–	–	–	–	–	–	−0.32***	0.035	−9.74
ΔAIC	−212			−59			−314		
ΔLRT	107			31			388		
Model comparison	$\chi^2(1) = 214.1$, $p < .001$			$\chi^2(1) = 61.1$, $p < 0.001$			$\chi^2(12) = 338.1$, $p < .001$		

Note. The analyses are based on 9,632 observations from 468 participants. *b* = unstandardized coefficients. AIC refers to the Akaike information criterion. LR refers to loglikelihood ratio. ΔAIC and ΔLR indicate the difference in AIC from each model to the next (e.g., AIC(Model 2)-AIC(Model 1). ΔAIC and ΔLR for Model 1 indicate the difference to the baseline model with random artist effects but no predictors. Smaller AIC values indicate a better fit. Higher LR indicates a better fit. Model comparison provides the results of ANOVA significance tests between the models, where each is compared to the previous one (and Model 1 to the baseline) *$p < .05$, ***$p < .001$.

high as that of the predicted general appeal ($b = 0.19$ vs. $b = 0.42$, respectively), this finding suggests that considering the personal preferences of individual consumers can incrementally increase predictive accuracy. Both effects remained stable when we included control variables in Model 3. In line with the highly significant effect of the general predicted appeal, the highly significant main effects of image personality suggest that there are certain combinations of image features that predict people's general image preferences, independent of their individual fit.

The results of Study 2 show that consumers' liking of an image can be predicted from the fit between their self-reported personality profile and the personality appeal of the image. Given that this effect was found to be incremental to the effect of general image appeal, the findings suggest that marketers can increase the aesthetic appeal of their marketing campaigns by taking the individual image preferences of their customers into account. However, image-person matching is only relevant for marketing if the increased liking of an image translates into an increased liking of the brand/product that the image is meant to promote. Study 3 was therefore aimed at demonstrating the value of image-person matching for personalized marketing more directly.

Study 3

Study 3 tested the hypotheses that participants would report more positive attitudes and purchase intentions toward brands that use images matched to participants' personality as part of their marketing campaigns. Similar to Study 2, we measured whether this effect added value above the effect of general image appeal.

Method

Image Selection and Personality Predictions

We used a subset of the images from Study 2 in the three categories "holiday," "beauty," and "phone" by selecting nine images in each category. Given that the number of people was found to be a strong predictor of personality appeal, we selected an equal number of images with no people, one person, and several people to avoid potential biases. In addition, we selected nine new images in the category "headphones" to guarantee that the effects were not unique to the images used in Study 2. The final set of stimuli therefore consisted of 36 images, in four product categories. Using the LASSO models developed in Study 1, we predicted the images' (a) general appeal as well as the (b) personality appeal for the five personality traits.

Assessment of Brand Attitudes and Purchase Intentions

We measured participants' attitudes toward brands using a commonly used 5-item scale. Participants were asked to indicate their opinions about the brands using a 7-point scale with the anchors "Unappealing/Appealing," "Bad/Good," "Unpleasant/Pleasant," "Unfavorable/Favorable," and "Unlikable/Likable." With a Cronbach's alpha of .97, the scale had excellent reliability. We measured participants' purchase intentions using a shortened 3-item version of an existing scale (Spears and Singh 2004). Participants were asked to report their intent to purchase from the brand using a 7-point scale with the anchors "Never/Definitely," "Definitely do not intend to buy/Definitely intend to buy," "Very low purchase intent/Very high purchase intent." A Cronbach's alpha of .98 indicated excellent scale reliability for these three items.

Participants and Procedure

Similar to Study 1, we aimed to recruit 400 participants on Amazon Mechanical Turk (final $N = 399$). The majority of participants (71%) reported to be between 25 and 44 years old, and 46% of participants indicated to be female. Participants were asked to indicate their opinion about a set of brands on the basis of the images that these brands were going to use as part of their upcoming marketing campaigns (e.g., "On the following pages you will see upcoming marketing campaigns for nine Beauty Brands. We would like you to indicate your opinions about the brands with the help of the statements and rating scales provided."). In order to avoid response biases arising from prior affinities with existing brands or the names of fake brands, participants were told the following: "As we do not want your responses to be influenced by your previous experiences with the brands, we have anonymized the brands and called them 'Brand A', 'Brand B' and so on." Using a within-subjects design, participants rated all of the 36 brand-image combinations, resulting in a total number of 14,364 ratings. To remain consistent with Study 2, we excluded ratings in the category beauty made by men, resulting in a final total of 12,030. In a second step, participants were asked to complete the 50-item IPIP personality questionnaire (Goldberg et al., 2006).

Calculation of Image-Person Fit and Prediction Models

We used the fit measure introduced in Study 2 to calculate the fit between participants and images. We applied multilevel modeling with the image-person fit (IP-fit) nested in participants and products (random intercepts) to estimate the effect of this fit on brand attitudes and purchase intentions. Similar to Study 2, Model 1 includes the predicted general appeal as a sole predictor of the image preference rating. Model 2 adds the IP-fit variable as a second predictor. Finally, Model 3 controls for participants' age and gender as well as the main effects of participant and image personalities. Similar to Study 2, we omitted the main effect of image Neuroticism due to the high (negative) intercorrelation between the predicted image appeal for Extroversion and Neuroticism.

Results

Table 4 displays the results of six multilevel models on brand attitudes (top half) and purchase intentions (bottom half; see Appendix S5 for the univariate correlations between variables). As the results in Table 4 show, general appeal was a highly significant predictor of participants' preference ratings (Model 1). The fit between the personality appeal of an image and the self-reported personality of a participant (IP-fit) was found to significantly predict preference ratings alongside of general appeal (Model 2). Although the predictive power of IP-fit is only about half as high as that of the predicted general appeal ($b = 0.31$ vs. $b = 0.56$, respectively), this finding suggests that considering the personal preferences of individual consumers can incrementally increase predictive accuracy. Both effects remained significant when adding all control variables in Model 2.

Similar to Study 2, we found strong main effects of image personality. Notably, some of the effects differed considerably in their magnitude and direction from those reported in Study 2. While a high level of image Extroversion, for example, was found to positively predict image appeal in Study 2 ($b = 0.55$, $t = 15.74$), it was found to negatively predict brand attitudes ($b = -0.44$, $t = -6.20$) and purchase intentions ($b = -0.30$, $t = -6.99$) in Study 3

Table 4
Multilevel Models Predicting Brand Attitudes (top) and Purchase Intentions (Bottom)

	Model 1			Model 2			Model 3		
Predictors	*b*	*SE*	*t*	*b*	*SE*	*t*	*b*	*SE*	*t*
Brand attitude									
Gen. appeal	0.54***	0.060	8.97	0.56***	0.060	9.34	0.61***	0.11	5.67
IP-fit	–	–	–	0.31***	0.067	4.60	0.34***	0.071	4.85
Gender	–	–	–	–	–	–	−0.41	0.40	−1.04
Age	–	–	–	–	–	–	−0.10	0.19	−0.54
Person-O	–	–	–	–	–	–	−0.37	0.21	−1.81
Person-C	–	–	–	–	–	–	0.051	0.21	0.24
Person-E	–	–	–	–	–	–	0.80***	0.21	3.70
Person-A	–	–	–	–	–	–	1.05***	0.22	4.87
Person-N	–	–	–	–	–	–	0.14	0.24	0.61
Extremity	–	–	–	–	–	–	0.40*	0.20	2.02
Image-O	–	–	–	–	–	–	0.032	0.089	0.36
Image-C	–	–	–	–	–	–	−0.0002	0.095	−0.003
Image-E	–	–	–	–	–	–	−0.44***	0.072	−6.20
Image-A	–	–	–	–	–	–	−0.056	0.070	−0.80
ΔAIC	−78			−19			−91		
ΔLR	40			11			57		
Model comparison	$\chi^2(1) = 79.86$, $p < .001$			$\chi^2(1) = 21.17$, $p < .001$			$\chi^2(12) = 114.71$, $p < .001$		
Purchase intention									
Gen. appeal	0.24***	0.035	6.69	0.25***	0.036	7.10	0.31***	0.064	4.83
IP-fit	–	–	–	0.20***	0.040	4.94	0.20***	0.042	4.68
Gender	–	–	–	–	–	–	−0.25	0.28	−0.90
Age	–	–	–	–	–	–	−0.25	0.13	−1.86
Person-O	–	–	–	–	–	–	−0.36*	0.14	−2.49
Person-C	–	–	–	–	–	–	−0.006	0.15	−0.042
Person-E	–	–	–	–	–	–	0.75***	0.15	4.98
Person-A	–	–	–	–	–	–	0.69***	0.15	4.61
Person-N	–	–	–	–	–	–	−0.049	0.16	−0.30
Extremity	–	–	–	–	–	–	0.13	0.14	0.03
Image-O	–	–	–	–	–	–	−0.004	0.053	−0.007
Image-C	–	–	–	–	–	–	0.065	0.057	1.16
Image-E	–	–	–	–	–	–	−0.30***	0.042	−6.99
Image-A	–	–	–	–	–	–	0.047	0.041	1.14
ΔAIC	−43			−22			107		
ΔLR	22			13			65		
Model comparison	$\chi^2(1) = 44.63$, $p < .001$			$\chi^2(1) = 24.35$, $p < .001$			$\chi^2(12) = 131.4$, $p < .001$		

Note. The analyses are based on 12,030 observations from 399 participants. b = unstandardized coefficients. AIC refers to the Akaike information criterion. LR refers to loglikelihood ratio. ΔAIC and ΔLR indicate the difference in AIC from each model to the next (e.g., AIC(Model 2)-AIC(Model 1). ΔAIC and ΔLR for Model 1 indicates the difference to the baseline model with random artist effects but no predictors. Smaller AIC values indicate a better fit. Higher LR indicates a better fit. Model comparison provides the results of ANOVA significance tests between the models, where each is compared to the previous one (and Model 1 to the baseline) *$p < .05$, ***$p < .001$.

(consistent with univariate correlations in Appendices S2 and S3). These deviations in main effects suggest that overall preferences in image personality might be influenced considerably by the specific characteristics of the sample. While Study 2 used a sample of young students from the United Kingdom and Germany, Study 3 was based on a sample of adults from the United States. The differences in the effects of image Extroversion across the two studies, for example, could therefore be explained by the fact that people's level of Extroversion is known to decline with age (Specht, Egloff, & Schmukle, 2011). Indeed, the average raw score in Extroversion was found to be significantly lower in the Mechanical Turk sample ($\bar{x} = 2.78$, $SD = 1.03$) than in the student sample ($\bar{x} = 3.30$, $SD = 0.78$;

$t(870) = 8.46$, $p < 0.001$). Image-person fit might hence be a more stable predictor than general image features related to personality.

Taken together, the results of Study 3 demonstrate the value of using image-person fit by showing that people do not only like matching images more but also report more favorable attitudes and purchase intentions toward brands that use matching images. This spillover effect of image perceptions to brand perception is crucial for marketers who want to use the mechanism of image-person fit to increase not only the appeal but also the effectiveness of their marketing campaigns. To avoid any confounding factors, we intentionally chose to use the image as the only indication for the personality of the brand. However, future research should test this spillover effect with existing brands that might already have an established brand personality. In this case, the images a company uses might be able to shift this brand image in a desired direction rather than defining it from scratch (e.g., making an extroverted brand even more extroverted).

General Discussion

The results of our three studies demonstrate the importance of personality differences in the context of consumers' aesthetic preferences for professional images. Study 1 showed that automatically extracted image features in combination with machine learning algorithms can be used to accurately predict the general appeal of an image as well as the appeal an image has to certain types of personalities (average prediction accuracy across all five traits is $r = .36$ with 10 out-of-sample predictions each). Studies 2 and 3 highlight the added value of understanding personal image appeal when it comes to predicting consumers' liking of an image or associated brand at the individual level. Study 2 showed that the fit between the personality of a consumer and that of an image can be used to predict that person's liking of a new set of images above and beyond the predicted general appeal of the image. Similarly, Study 3 showed that image-person fit does not only affect a person's liking of an image but also influences their attitudes and purchase intentions toward brands that use images of different characteristics as part of their marketing campaigns. Importantly, the effect of personality-matching was found to be incremental to the predictive power of general appeal. This suggests that, while general image appeal is a powerful predictor of how much consumers are going to like an image, marketers can further improve on the effectiveness of their personalization efforts by characterizing images based on how appealing they are to consumers of specific psychological profiles.

Our findings complement the existing literature on personality-tailored communication which shows that the persuasiveness of language-based communication can be increased by tailoring messages to people's personality characteristics (Hirsh, Kang, & Bodenhausen, 2012; Moon, 2002; Wheeler, Petty, & Bizer, 2005). For example, an extroverted person is more likely to be interested in a rather neutral product (e.g., a phone or a perfume) if the marketing messages used to promote the product imply sociable, exciting, or stimulating characteristics (e.g., highlighting "excitement" or "being in the spotlight," see Hirsh et al., 2012). While the importance of personality in language-based communication is hence well established and researched, our findings provide a starting point to extend this work to the context of visual communication.

Practical Implications

As we have stated in Introduction, the findings of this article contribute to the existing literature by providing a new practical approach to leveraging personality-matching in applied marketing contexts. The ability to automatically predict which image is going to be most appealing to a particular individual promises to help marketers further personalize their advertising material. However, it should be noted that we consider personality-matching in the context of advertising images as a second step in the creation or selection of advertising content, and an add-on to the existing creative process. That is, the first step in selecting advertising images will always be to identify a set of images that fit the general content of what is being advertised as well as branding and broader vision of the company. Only once this set of suitable images is identified does personality-matching come into play by selecting not only "a" suitable image for a particular customer, but "the most" suitable one.

In order to make image-person fit a viable component of real-life, large-scale communication, it is necessary to combine the automatic predictions of image appeal with an automatic assessment of consumers' psychological traits. In fact, while the assessment of personality with the help of traditional psychometric questionnaires is tedious, expensive, and impractical in the context of large-scale digital communication, recent research suggests that consumers' psychological traits can be predicted from digital footprints such as the contents of personal websites (Marcus et al., 2006), Facebook or Twitter profiles (Kosinski et al., 2013; Quercia, Kosinski, Stillwell, & Crowcroft, 2011; Youyou et al., 2014), or language used in social media (Park et al., 2014; Schwartz et al., 2013). As the digital assessment of psychological traits becomes more widespread and readily available (e.g., through third-party providers such as IBM StatSocial or VisualDNA), businesses will be able to adapt the visual aesthetics of their communication (e.g., their website or marketing campaigns) to consumers' personality profiles in real time, at scale, and at little to no cost (compare for initial evidence supporting the effectiveness of such an approach: Hauser, Urban, Liberali, & Braun, 2009; Matz, Kosinski, Nave, & Stillwell, 2017). While these new types of automatic personality assessments hence provide opportunities for personality-based image matching, they are also associated with a number of ethical challenges related to data protection and privacy. Marketers should carefully weigh those challenges when considering the implementation of personality-matching (e.g., compare Kosinski et al., 2015; Matz et al., 2017).

When considering the commercial value of matching images to consumers' personality profiles, it is important to note that the reported effects are relatively small. For example, holding all other variables constant, shifting personality fit from the 15^{th} to the 85^{th} percentile increased consumers' intention to purchase by 0.1 standard deviation (Study 3). However, when implemented at a scale that is as large as that of most multinationals' marketing campaigns even small improvements over existing approaches could lead to meaningful gains. This is particularly true when considering the fact that consumers are often choosing between competing products or service providers. While the winning seller takes it all, the loser goes empty-handed. Hence, making a company's website or marketing campaign even a little bit more appealing than that of the competition might be the deciding factor in whether a consumer buys from one company or the other. In addition, the accuracy with which we can predict the personality-related appeal of images—and with it the practical usefulness of our initial findings—is likely to increase when using more comprehensive feature sets and advanced computer vision techniques (see Limitations section next). The fact that effects are small means that developing technologies and capabilities for personality-matched image selection is likely to pay off primarily for companies that have a large enough marketing volume to justify the upfront costs related to the automatic prediction of both image and consumer personality.

Limitations and Future Research

The research presented in this article has several limitations that should be addressed by future research. First and foremost, we used a selective set of image features that were mainly focused on low-level features (e.g., contrast and saturation) rather than high-level features (e.g., the object or activity displayed in an image). From all the possible objects that could be featured in an image, the algorithm we used allowed us to only detect nine distinct objects (e.g., "bicycle" or "cat") as well as features related to people and faces. While people are likely to consciously evaluate high-level features (e.g., there are people dancing), they are much less likely to consciously notice and evaluate low-level features (e.g., whether all the lines go in the same direction), making their influence subtler—and potentially weaker—than that of high-level features. Besides from placing a stronger emphasis on the image content, the accuracy of predicting personality appeal could be further increased by applying advanced deep learning approaches (LeCun, Bengio, & Hinton, 2015). While manually defined aesthetic features are limited by human imagination, deep learning makes it possible to explore the effectiveness of features that have not yet been discovered by automatically extracting patterns on the pixel level (Lu, Lin, Jin, Yang, & Wang, 2014).

Second, while the findings of Study 3 provide initial evidence that people's enhanced liking of images translates into more favorable brand attitudes and purchase intentions, future research should test this proposition in settings that resemble actual marketing contexts more closely. That is, we aimed to control for potential confounds by limiting the information people received about the brand to the image only, keeping all other information about the brand neutral. However, in order to demonstrate that our findings hold in a more naturalistic setting in which people's perception of the brand is influenced by a combination of factors (e.g., prior experience, logo, advertising copy), future research should replicate our findings using more realistic ads.

Conclusion

Taken together, we have demonstrated the scientific as well as commercial value of understanding and predicting image appeal on the individual as well as the group level. By addressing the question of "How appealing is this image to this particular consumer?" we were able to predict a person's liking of an image as well as their attitudes and purchase intentions toward brands above and beyond general image appeal. As personalized one-to-one communication continues to grow and the automatic assessment of personality from digital footprints becomes widely accessible, businesses can use these insights to gain competitive advantage by better serving their customers' individual needs and preferences. While most current approaches to personalized communication focus on *what* is communicated to consumers (e.g., which product is advertised, or which article is presented on the landing page), our findings highlight the potential of customizing *how* businesses communicate this content. Beyond getting the content right, this additional "personal touch" could turn out to be crucial in building strong and successful long-term relationships with consumers.

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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's website:

Appendix S1. Feature extraction and predictive modeling guide.

Appendix S2. Image categories used in Study 1.

Appendix S3. LASSO regression.

Appendix S4. Univariate correlations of variables used in the analysis of Study 2.

Appendix S5. Univariate correlations of variables used in the analysis of Study 3