American Psychological Association DIVISION 10 Psychology of Aesthetics, Creativity, and the Arts

1931-3896/18/$12.00

2018, Vol. 12, No. 4, 399–431
http://dx.doi.org/10.1037/aca0000187

Quantifying Visual Aesthetics Based on Processing Fluency Theory: Four Algorithmic Measures for Antecedents of Aesthetic Preferences

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Humans are inherently evaluative beings whose affective system is predisposed to continuously and efficiently produce spontaneous preferences regarding surrounding stimuli. These preferences guide us through the physical world by indicating which stimuli to approach and which to avoid. Vision is the key sense to provide the necessary input for this superficial evaluative process that focuses on the exterior appeal of stimuli. To allow a better understanding of the link between visual input and evaluative response, the present article aims to identify visual antecedents of immediate aesthetic preferences. In particular, we propose a set of 4 algorithmic measures that automatically extract the low-level visual stimulus properties that are predictive of aesthetic preferences according to processing fluency theory: visual simplicity, visual symmetry, visual contrast, and visual self-similarity. In 3 studies, we demonstrate the impact, the relative importance, and the validity of these 4 visual characteristics for understanding aesthetic preferences. We examine the link between the 4 measures and aesthetic liking using a large pool of digital abstract artworks in Study 1. In Study 2, we experimentally replicate the findings of the first study to confirm their robustness. To generalize the results, Study 3 examines preferences for landscape photographs using secondary data of an online photo community. Furthermore, we built a database of 620 abstract digital artworks that can be used to benchmark future developments in measuring antecedents of visual aesthetics and that can serve as a pool of stimuli for experimental research on aesthetics.

Keywords: visual preferences, liking, empirical aesthetics, image statistics, processing fluency

> "Measure what is measurable, and make measurable what is not"
> —Galileo Galilei (1564–1642)

We fall in love at first sight (Back, Schmukle, & Egloff, 2010). We prefer nicely wrapped gifts (Howard, 1992). We even depend primarily on visual information when making judgments about music performances (Tsay, 2013). As these examples illustrate, humans are inherently evaluative beings (Zajonc, 1980) whose affective system continuously produces immediate visual preferences. Accordingly, the visual system must be capable of extracting core visual stimulus characteristics that are linked to spontaneous aesthetic preferences (Graf & Landwehr, 2015).

Among other explanations (e.g., Chubb, Landy, Nam, Bindman, & Sperlin, 2004), low-level visual stimulus characteristics that facilitate perceptual processing (e.g., visual simplicity, visual symmetry, and visual contrast) have been proposed to trigger aesthetic liking because fluent processing is a pleasurable experience (Reber, Schwarz, & Winkielman, 2004). Visual stimuli can vary noticeably in such low-level characteristics; however, a standardized approach to objectively capture this potentially explanatory variance is currently missing in empirical aesthetics. Instead, the majority of studies employ subjective ratings of percepts of these stimulus characteristics (e.g., Hekkert, Snelders, & van Wieringen, 2003; Orth & Crouch, 2014). With such subjective ratings, though, evidence of a link between visual stimulus characteristics and aesthetic liking is indirect, mostly correlational, and may therefore suffer from unobserved variables and potential confounders that bias statistical model estimates and error terms (Bullock, Green, & Ha, 2010). Further, based on the argument developed by Fiedler (2014) that the explanatory value of a theory increases with greater conceptual distance between predictor variable(s) and outcome variable(s), the focus on intrapsychic variables in prior research on aesthetics may constrain the advancement of theories on empirical aesthetics. Moreover, most studies cover only one visual characteristic to predict aesthetic liking, and very few studies cover a maximum of two. We are not aware of any study that features more than two visual characteristics at the same time, which restricts the evaluation of the relative importance of visual characteristics and inhibits the identification of the unique variance components of aesthetic liking that can be explained by visual

This article was published Online First October 18, 2018.
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The authors thank Manuel Schneitz and Laura Graf for their support in selecting pictures for the database, and Roland Deutsch, Thomas Otter, and Gregor Hayn-Leichsenring for helpful comments on an earlier draft of this manuscript.
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characteristics (i.e., the effect of one visual characteristic on aesthetic liking with the effects of other characteristics partialed out).

The aim of the present article is to overcome these shortcomings of prior research by proposing a set of *objective,* algorithmic measures that were selected based on processing fluency theory. To validate the measures, we conducted three empirical studies. First, we built a database containing 620 pictures of digital abstract artworks and collected subjective aesthetic liking ratings of these pictures. Based on the statistical properties of the digital image files of these pictures, a set of procedures programmed in the statistical programming language "R" computed four strictly objective measures per picture (visual simplicity, visual symmetry, visual contrast, and visual self-similarity), which were used to predict subjective aesthetic liking judgments. A second study replicated the link between objective measures and aesthetic liking in an experimental setup. In a third study, we tested the generalizability of our findings by predicting how often landscape photographs would be viewed on a popular image hosting website based on the four measures.

We aim to contribute to the literature on empirical aesthetics in several ways. First, we merge insights from different research streams to propose four strictly objective measures of visual characteristics that are antecedents of aesthetic liking judgments. These measures require only digital image files and have the advantage of being exogenous stimulus variables instead of endogenous perceptions of stimuli. Second, by incorporating four measures into one statistical model, we can quantify the relative importance of key principles of visual aesthetics, allowing future research to prioritize these visual characteristics on an empirical basis. This knowledge may also help in advancing theories on the mechanisms underlying aesthetics. Third, we provide straightforward algorithmic operationalizations of these four visual antecedents that can be used as a toolbox of objective measures of visual aesthetics in diverse scientific fields.

We organize the remainder of the article as follows. First, we review the literature on the proposed process underlying aesthetic preferences, namely, processing fluency theory, and describe how our four algorithmic measures are theoretically motivated. Next, we describe the computational mechanics of the four measures. In the empirical part, we report the results of three studies that examine the link between the objective measures and subjective aesthetic preferences. Finally, we discuss our approach and our results, and we provide recommendations for applications and future research.

Aesthetic Preferences and Fluency Theory

In the current research, we focus exclusively on aesthetic preferences that arise from the visual configuration of a stimulus. Hence, any content or meaning of the stimulus is not considered; we deliberately limit our scope to variations in low-level stimulus characteristics and their link to aesthetic preferences. Such preferences are commonly reflected by spontaneous aesthetic liking judgments, which is our key dependent variable. To explain the psychological mechanism that yields aesthetic preferences according to our understanding and to derive our hypotheses, we exclusively rely on processing fluency theory (Reber, Schwarz et al., 2004) because this theory makes concrete predictions for low-level stimulus characteristics that can be measured objectively. For reasons of parsimony, we do not discuss other theoretical accounts of aesthetic preferences (e.g., Hekkert et al., 2003; McManus & Stöver, 2014).

Processing fluency theory makes the key prediction that the ease of (perceptually) processing a stimulus influences the aesthetic liking of the stimulus (Reber, Schwarz et al., 2004) because higher fluency (and, hence, easier processing) is inherently positive and experienced as gut-level positive affect (Winkielman & Cacioppo, 2001). Two reasons may be responsible for this positive affect: (a) fluent processing indicates progress toward the goal of recognition and interpretation of a stimulus, and (b) fluent processing may be a signal that the stimulus has been faced before or is familiar in some way, thus decreasing the uncertainty triggered by the stimulus (Schwarz, 2004; Winkielman & Cacioppo, 2001). This idea has been the subject of numerous studies over the last decade, and the impact of fluency on evaluative judgments has been demonstrated in a wide range of contexts (Alter & Oppenheimer, 2006; Labroo & Kim, 2009; Landwehr, Wentzel, & Herrmann, 2013; Lee & Labroo, 2004).

Importantly, research has shown that the experience of fluency can be determined by core visual characteristics of a stimulus that are nonspecific to its content (Reber, Schwarz et al., 2004). Three objective, low-level features of stimuli have been proposed that result in increased fluency. In particular, perceptions of visual simplicity, symmetry, and contrast have been found to facilitate processing and to increase aesthetic liking (Reber, Schwarz et al., 2004). In the following, the specifics of these three visual characteristics and their relationship with aesthetic liking are described in more detail. Furthermore, a recent study suggests that the visual self-similarity of a stimulus can be linked to processing fluency (Joye, Steg, Ünal, & Pals, 2016). We therefore add the concept of self-similarity as a complementary visual characteristic to the study of pleasure-driven aesthetic liking. In contrast to prior research, we introduce strictly objective, algorithmic measures of all four stimulus characteristics.

Theoretical Background of Visual Characteristics

Visual Simplicity

Visual simplicity can be defined as the amount of information a stimulus contains[1] (Garner, 1974). Following this understanding, simpler stimuli contain less information and require less processing capacity than complex ones do. Accordingly, a monotonic positive relationship between visual simplicity and aesthetic preference would be expected by fluency theory (Palmer, Schloss, & Sammartino, 2013). Research has demonstrated this relationship, for example, with olfactory cues in a retail setting (Herrmann, Zidansek, Sprott, & Spangenberg, 2013). Other studies, however, show an initial increase in preference with increasing complexity up to some optimum level and a subsequent decrease of preference with additional complexity. This curvilinear relationship is described most prominently by Berlyne (1970). He argues that there

[1] Most researchers label this visual characteristic visual *complexity* instead of visual simplicity. However, because we base our measures on fluency theory, we use the term *simplicity* because, according to fluency theory, simplicity aligns with processing fluency and should have a positive influence on aesthetic preferences.

is an optimal arousal level for which preference is highest, and stimuli that are either too simple or too complex result in arousal levels that are too low or too high, respectively. There are also several more recent studies which show monotonic positive effects of complexity (i.e., a negative effect of simplicity) for Renaissance paintings (Aleem, Correa-Herran, & Grzywacz, 2017), International Affective Picture System (IAPS) pictures (Marin & Leder, 2013), advertisements (Pieters, Wedel, & Batra, 2010), and car designs (Landwehr, Labroo, & Herrmann, 2011). Hence, empirical findings on the relationship between simplicity and aesthetic preference are not as straightforward as they are for other visual characteristics and may require more advanced assumptions about the underlying processes. Nevertheless, based on processing fluency theory, we predict a positive effect of simplicity on aesthetic liking in our research.

Visual Symmetry

Visual symmetry can be formally defined as the similarity of parts of an image under transformations such as translation or reflection, usually restricted to an Euclidean plane (Wagemans, 1997). In practical applications, symmetry is usually understood as the extent of similarity between two halves of an image mirrored along a central axis, that is, mirror (reflective) symmetry (e.g., Bajaj & Bond, 2018). Humans have an innate preference for symmetry (Etcoff, 1999), and the human visual system is exceptionally good at detecting symmetry (Wagemans, 1997). The most prevalent explanation for this effect is that symmetry reflects biological fitness (Rhodes, 2006) because it is connected to the healthy ontogenetic development of the body (Thornhill & Gangestad, 1999). Therefore, symmetry is particularly associated with the attractiveness of human faces (Rhodes, Proffitt, Grady, & Sumich, 1998). Notably, the effect of symmetry can also be found in abstract shapes (Jacobsen & Höfel, 2002; Tinio & Leder, 2009), art (Mayer & Landwehr, 2014), brand logos (Bajaj & Bond, 2018), product design (Bloch, 1995), and the field of human-computer interaction, where an advantage of vertical symmetry for websites has been found with regard to intuitive beauty (Tuch, Bargas-Avila, & Opwis, 2010). To explain these preferences for symmetry in the domain of artificial stimuli, one can refer to an overgeneralization of the innate, evolutionary symmetry preference. That is, humans cannot simply switch off their biological preference disposition; instead, they transfer it automatically to other objects (Voland, 2003). In addition to this biological explanation, preferences for symmetry in artificial stimuli have been successfully linked to higher levels of experienced processing fluency (Graf, Mayer, & Landwehr, 2018; Mayer & Landwehr, 2014), as proposed by this article's overarching theoretical framework. We therefore expect a positive effect of symmetry on aesthetic preferences in our studies.

Visual Contrast

Visual contrast is not coherently defined in the literature (Peli, 1990). Most definitions are merely based on the statistical measurement of contrast and include differences in luminance between the components of a picture (e.g., Weber contrast; cf. Whittle, 1994). Thus, contrast essentially is the dissimilarity between components within a picture, making an object like text for example distinguishable from its background (i.e., figure-ground contrast). Visual contrast, specifically figure-ground contrast, has been linked in a rich set of empirical studies to processing fluency and fluency-related variables. The recognition speed of stimuli, for example, is faster for stimuli high in figure-ground contrast (Checkosky & Whitlock, 1973). Contrast also enhances the detection of briefly presented words (Reber, Wurtz, & Zimmermann, 2004). Moreover, higher figure-ground contrast has been shown to increase aesthetic liking (Reber, Winkielman, & Schwarz, 1998).

A major shortcoming of most previous studies is that they concentrate only on figure-ground contrast rather than the overall contrast of the stimulus, usually because the employed visual stimuli are artificial patterns on interchangeable backgrounds. Very few studies have investigated the effect of the overall contrast of natural or human-made scenes or even real-life products. One example is a study about the effect of image quality degradation on the aesthetic judgments of high-quality photographs (Tinio, Leder, & Strasser, 2011), which finds that overall contrast is the most influential determinant of aesthetic liking (compared with sharpness and grain), with higher contrast resulting in higher liking scores. Hence, we likewise expect contrast to have a positive effect on aesthetic liking in our research.

Visual Self-Similarity

Before we formally define visual self-similarity, it is worth considering a few demonstrative examples of the stimulus domain that provides the richest set of self-similar visual patterns: nature. Nature tends to be efficient, which can be witnessed when looking at clouds, holding a fern leaf in your hand, or eating Romanesco broccoli. What these examples have in common is repeating patterns that are self-similar, or so-called fractal properties. The term "fractal" was introduced by the mathematician Benoit Mandelbrot, who realized that nature is full of fractal geometry (Mandelbrot, 1982). Accordingly, fractals have been described as "fingerprints of nature" (e.g., Taylor, Micolich, & Jonas, 1999). Interestingly, the idea of fractal geometry revolutionized modern computer animation because the algorithms behind very complex visual scenes (such as explosions or mountain ranges) efficiently implement only the basic fractal properties of these scenes, which are simply repeated many times to produce the complex-looking final outcome.

In simple terms, self-similarity means that zooming in and out of an image reveals the same repeating visual pattern (i.e., scale invariance). Self-similarity has received increasing attention in recent years and has been studied in pictures of artificial monochrome patterns (Street, Forsythe, Reilly, Taylor, & Helmy, 2016), architecture (Braun, Amirshahi, Denzler, & Redies, 2013), print advertisements (Braun et al., 2013), cartoons (Koch, Denzler, & Redies, 2010), images of natural scenes (Field, 1987; Simoncelli, 2003), and aesthetic writings (Melmer, Amirshahi, Koch, Denzler, & Redies, 2013).

In the present context, it is important to note that a main characteristic of natural scenes is that their Fourier power spectrum (Figure A1 in Appendix A) is scale invariant. This means that it is possible to zoom in and out of an image of a natural scene with little change to the relative strength of coarse and fine structures (Mallon, Redies, & Hayn-Leichsenring, 2014). This visual property can be linked to processing fluency because our visual system is adapted to process natural scenes efficiently (Simoncelli, 2003).

Accordingly, the fluent processing of natural scenes induces pleasure, and pictures with statistical properties similar to those of natural scenes (i.e., self-similar or fractal images) are characterized by ease of processing and the experience of pleasure, respectively (Fernandez & Wilkins, 2008; O'Hare & Hibbard, 2011). In a similar vein, it has been speculated that visually pleasing pictures follow universal regularities such that they can be processed efficiently by the human visual system (Zeki, 1999). A recent study suggests that self-similarity, indeed, relates to perceptual processing fluency (Joye et al., 2016), which constitutes a process explanation for the link between visual self-similarity and aesthetic preferences in accordance with our theoretical framework. Therefore, we hypothesize a positive effect of self-similarity on aesthetic liking in the current research.

Fluency-Based Visual Aesthetics

Simplicity, symmetry, and contrast have been proposed as theoretical constructs by the processing fluency theory of aesthetic pleasure (Reber, Schwarz et al., 2004). However, objective measures of these constructs are not proposed by the original framework. Self-similarity, in contrast, can be objectively assessed with previous approaches (e.g., Koch et al., 2010; Melmer et al., 2013) but has not yet been integrated into an overarching theoretical framework. Only one recent study implies a connection between self-similarity and processing fluency (Joye et al., 2016). The present research connects these streams of research by using the fluency framework as the guiding theoretical account that motivates four objective, algorithmic measures of visual antecedents of aesthetic liking. As described above, there is convincing evidence that low-level visual stimulus characteristics shape aesthetic liking. However, almost all prior studies on aesthetic liking consider only one or a maximum of two of these variables at a time and do not simultaneously study the effects of several or all of these variables.

This very common approach assumes that the discussed determinants of aesthetic liking are uncorrelated and that the measurement/manipulation of one variable is independent of all other variables. Otherwise, an unbiased statistical estimation of the effects of the visual variables on aesthetic liking would not be possible. However, the question of whether and to what extent these four determinants of aesthetic liking are correlated is empirical in nature and can only be answered if all four variables are considered simultaneously. Moreover, if they are correlated, unbiased estimates of their effects on aesthetic liking can only be expected if a statistical model includes the correlated ones. Likewise, the relative importance of the variables can only be assessed if all four are included in one statistical model. The present research therefore discusses objective, algorithmic measures of antecedents of aesthetic liking that we propose based on fluency theory. We examine these measures' relation and relative importance. The R code to implement the four measures is available upon request from the authors and will made publicly available on the Comprehensive R Archive Network (CRAN).

Four Algorithmic Measures for Visual Aesthetics

An Algorithmic Measure of Visual Simplicity

Perception research and algorithmic information theory (Donderi, 2006) indicate that picture simplicity can be measured accurately by image compression rates because complex images are denser and have fewer redundancies than simple images do (see Figure 1). Previous studies have shown that the inverted (i.e., multiplied by −1) file size of an image compressed by a compression algorithm (such as Deflate, which is the default on most operating systems when using ZIP compression) is a valid indicator of visual simplicity because compression algorithms are based on the use of visual redundancies to reduce the file size (Forsythe, Nadal, Sheehy, Cela-Conde, & Sawey, 2011; Landwehr et al., 2011). Although this approach has been proven to be useful, it has several drawbacks that call for improvement. First, compression algorithms such as ZIP do not depict redundancies of different orientations equally (i.e., horizontal vs. vertical redundancies differ in their compression rates; for an example, see Appendix B). Second, the measure is sensitive to the absolute image resolution and thus requires highly standardized stimulus material. Third, the measure has no natural meaning, which impedes a substantial interpretation.

Thus, we propose an improved version of such a compression-based simplicity measure that calculates objective simplicity as one minus the ratio between the compressed and the uncompressed image file size. By taking the ratio, the measure becomes robust against differing image resolutions. Because the ratio depicts complexity, we subtract the ratio from one to obtain a measure for simplicity. The range of the resulting simplicity values s is $0 \leq s < 1$, which gives the resulting measure a natural interpretation. We apply this approach to both the original images and the images rotated by 90 degrees and take

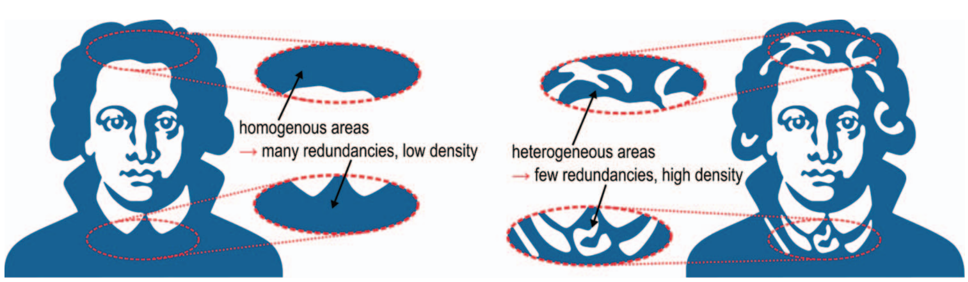

Figure 1. Illustration of the visual simplicity measure. Simple images are characterized by homogenous areas that consist of many redundancies and a low density (left). Compression algorithms identify these redundancies, resulting in reduced file sizes. More complex images, in contrast, typically are composed of more heterogeneous areas that contain only a few redundancies (right). See the online article for the color version of this figure.

the minimum value as our final measure of simplicity so that the orientation of redundancies does not bias the measure.

In accordance with prior research (Landwehr et al., 2011), we use the ZIP/deflate compression algorithm applied to color images as our default measure. Additionally, we test the GIF and JPG file formats as alternative image compression methods (cf. Forsythe et al., 2011) using ImageMagick with the software's default value for JPG compression.

An Algorithmic Measure of Visual Symmetry

In all our studies, we focus only on vertical symmetry as the experientially most dominant and most easily detectable type of symmetry (Corballis & Roldan, 1975; Palmer & Hemenway, 1978; Wagemans, 1997; Wenderoth, 1994). Similarly, we focus only on global symmetry (i.e., we do not measure local symmetries). Accordingly, visual symmetry can be measured based on the correlation of pixel grayscale values of corresponding pixels left and right of the central vertical image axis (Mayer & Landwehr, 2014). That is, a picture is more vertically symmetrical (i.e., mirrored on the vertical axis) the closer the corresponding pixels left and right of the central axis are to each other with regard to their grayscale values (see Figure 2). However, this simple approach has two shortcomings we would like to address by proposing an advanced measure for visual symmetry.

First, this approach is limited to greyscale images or images converted to greyscale and thus ignores any color information. To take color into account, we calculate symmetry as described above separately for each color channel (red, green, blue). Then, we aggregate the three symmetry values into a single overall symmetry value using the Luma color coding system. The Luma coding system follows the ITU-R BT.601 standard and is the default for most color-to-grayscale conversion algorithms (such as the rgb2gray functions from MATLAB and OpenCV) because it accounts for human luminosity perceptions (i.e., higher sensitivity to green colors). In particular, the overall symmetry value of an image is calculated as a weighted mean of the values of the three color channels: $0.299 \times \text{red} + 0.587 \times \text{green} + 0.114 \times \text{blue}$ (see Figure C1 in Appendix C for an illustration).

Second, the perceptual mirror axis is not necessarily exactly in the middle of a picture. To account for random variations in the mirror axis, we measure the symmetry of an image using different positions of the mirror axis. In particular, we shift the mirror axis up to 5% of the image width to the left and to the right in steps of 1% of the image width. For an image with a width of 200 pixels, for example, we move the mirror axis of the image by two pixels (1% of 200 pixels), four pixels (2%), six pixels (3%) eight pixels (4%), and 10 pixels (5%) to the left and to the right of the vertical middle axis and calculate 10 additional symmetry values as explained above (when moving the mirror axis, the nonmirrorable pixels on the border of the resulting wider side are ignored). The final symmetry value for each color channel is thus the maximum of all 11 calculated symmetry values.

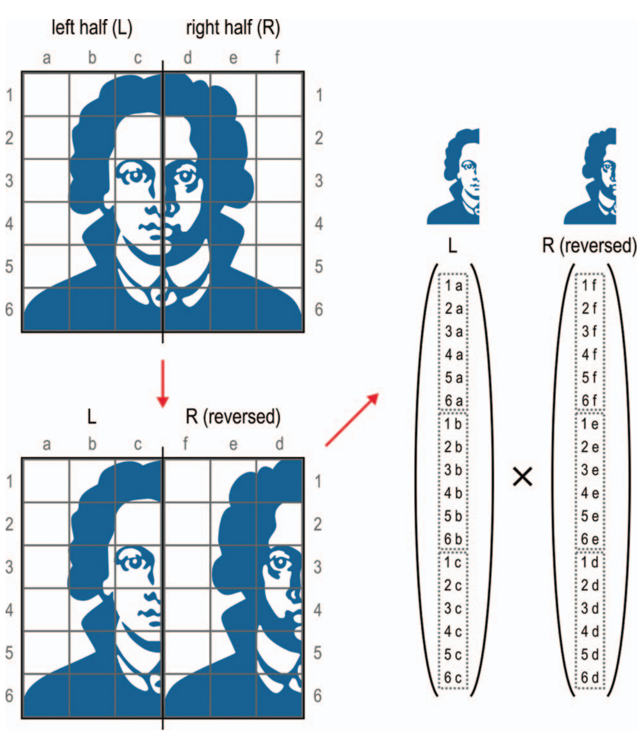

Figure 2. Illustration of the visual symmetry measure. Essentially, the algorithm divides an image into two parts, stores the pixel intensity values into two vectors (one value per vector element), and correlates these vectors. By flipping the right half beforehand, corresponding columns are compared with each other. The present research only considers vertical symmetry. See the online article for the color version of this figure.

An Algorithmic Measure of Visual Contrast

To measure objective contrast, we use the root-mean-squared (RMS) contrast of an image (see Figure 3), which is the standard deviation of the grayscale pixel intensities (Peli, 1990). To the best of our knowledge, our study is the first to link an objective measure of visual contrast to the fluency literature. RMS contrast has the advantage of being independent of the spatial frequency of the image as well as the spatial distribution of contrast in the image. More importantly, RMS contrast reliably predicts human contrast detection thresholds (Bex & Makous, 2002; Frazor & Geisler, 2006). Because the common RMS contrast can only be applied to greyscale images and ignores any color information, we again apply the computational approach according to the Luma coding system described for the symmetry measure to account for color. In particular, we calculate the RMS contrast separately for each color channel and compute the overall picture contrast as the weighted mean of the three channels (see the description of the symmetry measure above).

An Algorithmic Measure of Visual Self-Similarity

The measurement of visual self-similarity is conceptually more complicated than the measurement approaches for the other three measures and requires analyzing the frequency distribution of an image's spatial frequencies. In particular, we analyze the Fourier power spectrum of an image, which corresponds to the frequency components into which a signal (in our case, an image) can be decomposed. In simple terms, this means determining how often the components of an image are represented and to what extent they account for the overall perception of the image (see Figure 4). Importantly, previous work has shown that images vary in the slope of their log-log Fourier power spectrum (e.g., Braun et al.,

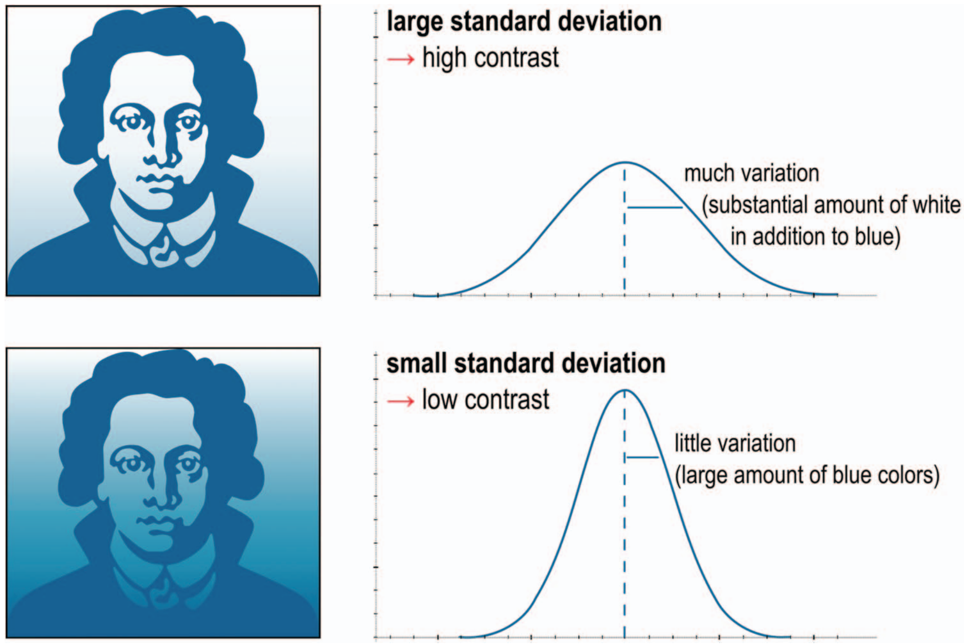

Figure 3. Illustration of the visual contrast measure based on the root-mean-squared (RMS) contrast. If an image has low contrast, there are more colors of the same type and hence little variation. If an image has high contrast, there are substantially different colors that create the perception of contrast and hence much variation. Thus, images with low contrast translate to a small standard deviation of the pixel intensities, and images with high contrast result in a large standard deviation. See the online article for the color version of this figure.

2013; Graham & Redies, 2010; Koch et al., 2010; Melmer et al., 2013) and that the slope of natural scenes with maximum fractal properties converges at −2 (Field, 1987; Redies, Hasenstein, & Denzler, 2007; Simoncelli & Olshausen, 2001). Following these insights, we calculate the slope of the log-log power spectrum using ordinary least squares (see Appendix A) and measure the self-similarity of an image with the following formula: self-similarity = abs(slope + 2) × (−1). Hence, the measure reaches its maximum value of 0 for a slope of −2 (indicating maximum scale invariance/fractal properties), and any deviation from −2 results in negative values that are more negative the higher the deviation from −2. As before, we account for color by calculating self-similarity separately for each color channel and computing a weighted mean according to the Luma coding system (see the description of the symmetry measure above).

Study 1

To test our measures, we built a database with 620 pictures (the Abstract Digital Artworks Database). We will first describe the background of this database, followed by a description of our statistical modeling approach, the results of our analysis, and a brief discussion of the findings.

Abstract Digital Artworks Database

The database consists of digitally created, colored images (pictures) from a single artist whose work can broadly be described as abstract digital artwork (see Figure D1 in Appendix D for examples). All images were cropped, downsized to a uniform dimension of 512 × 512 pixels, and saved as uncompressed bitmap image files to avoid artifacts in any analysis due to compression or different image sizes (see Appendix D for details).

For each colored, cropped picture, ratings of aesthetic liking ("*How much do you like this picture?*;" horizontal slider (a visual analog scale with an internal resolution of 100 steps) from *not at all* to *very much*) and subjective fluency experience ("The process of thinking about this picture . . . (a) *is difficult for me* versus *comes naturally to me*, (b) *is exhausting for me* versus *is easy for me*, (c) *I perceive to be sluggish* versus *I perceive to be smooth*;" again on a horizontal slider, α = .917) were obtained. These ratings were based on an Amazon MTurk sample of 2,380 subjects (47.7% female; M_{age} = 31.9, SD_{age} = 11.4), of whom 1,163 (48.9%) rated random subsets of the picture database on aesthetic liking and 1,217 (51.1%) rated random subsets of the picture database on subjective processing fluency. In particular, each participant rated self-paced a random subset of 60 pictures (liking evaluation) or 20 pictures (fluency evaluation), which were drawn from the 620 pictures included in the database, to maintain his or her workload at an acceptable level (i.e., a maximum of 60 evaluations per person). Thus, for each picture, there are, on average, 112.55 unique ratings of aesthetic liking (SD = 8.94; Min = 88; Max = 138) and 39.26 unique ratings of subjective processing fluency (SD = 5.94; Min = 24; Max = 61). In addition to evaluating either liking or fluency, participants stated their art expertise ("*How much do you consider yourself an art expert?*"; horizontal slider with 100 continuous increments from *not at all* to *very much*) and basic demographic questions (i.e., gender, age, education).

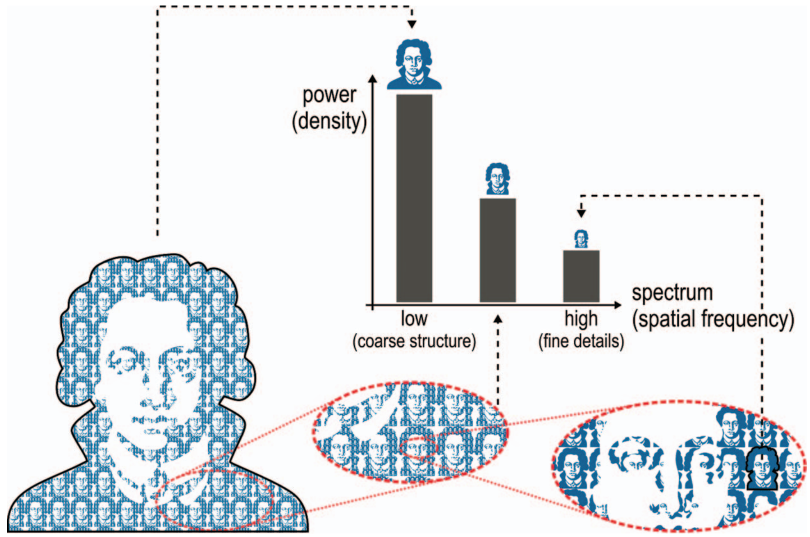

Figure 4. Illustration of the visual self-similarity measure. This schematic portrait has repeating patterns: The overall portrait consists of little portraits, which again comprise the same little portraits (oversimplified example of self-similarity). If you look at the big portrait on the left, the foremost and primary perception is the overall portrait, not an assembly of little portraits. Hence, the details (which are coded in high spatial frequencies in our perception) do not substantially account for the overall impression of the image and thus have low power in the spectral density plot. More dominant is the coarse structure, which is coded in the low frequency spectrum. Self-similarity is typically associated with a specific distribution of the spectral power (it falls off with the spatial frequencies according to a power law). See the online article for the color version of this figure.

Analysis

For all 620 pictures in the database, we calculated visual simplicity, visual symmetry, visual contrast, and visual self-similarity based on the proposed algorithmic measures.[2] Appendix E shows descriptive plots for all variables used in Study 1. To test the independence of the measures, we computed pairwise Pearson correlations between all measures. This analysis was conducted on the stimulus level and thus included 620 observations. To determine the unique effect of each of the variables on aesthetic liking when controlling for the effects of all others and to estimate their relative importance, we ran Linear Mixed Models (LMM; Fitzmaurice, Laird, & Ware, 2004) with REML-fitted estimators. This analysis was conducted on the participant level and included 1,163 cases with 60 nested observations (i.e., pictures) per person. The employed LMM approach controls for the nested data structure by estimating both fixed and random effects. In particular, because the subjects in the database evaluated not one but several pictures, the error terms of the individual observations are not independent from each other. To analyze the data, we relied on the lmer() function of the lme4 library in R (Bates, Mächler, Bolker, & Walker, 2015). We used the lmerTest library (Kuznetsova, Brockhoff, & Christensen, 2016) for significance testing. Taking into account the recommendations of Barr, Levy, Scheepers, and Tily (2013) and Bates, Kliegl, Vasishth, and Baayen (2015), we included crossed random intercepts per participant and per picture in the models because the liking ratings were nested within participant i and also nested within picture j. Additionally, because the employed aesthetic measures have different (and partly not naturally interpretable) scales, we z-transformed all predictor variables prior to the LMM analyses to allow for a meaningful interpretation of the regression coefficients.

We ran six different models. For all models, b indicates the fixed effects, u indicates the random effects, and ε indicates the residual. The first three models comprised only the four aesthetic measures as predictors. They differed only with respect to the image compression algorithm that was used to calculate simplicity (ZIP/deflate vs. JPG vs. GIF), and all had the following form:

$$\begin{aligned}\mathrm{LIKING}_{ij} = b_0 + b_1 \times \mathrm{SYMMETRY}_j + b_2 \times \mathrm{SIMPLICITY}_j \\ + b_3 \times \mathrm{CONTRAST}_j + b_4 \times \mathrm{SELF\text{-}SIMILARITY}_j \\ + u_{0i} + u_{0j} + \varepsilon_{ij.}\end{aligned} \tag{1}$$

The remaining three models additionally included a participant's art expertise as a control variable (main effect and interactions with the four aesthetic measures). Again, the three models only differed with respect to the simplicity measure and had the following form:

$$\begin{aligned}\mathrm{LIKING}_{ij} = b_0 + b_1 \times \mathrm{SYMMETRY}_j + b_2 \times \mathrm{SIMPLICITY}_j \\ + b_3 \times \mathrm{CONTRAST}_j + b_4 \times \mathrm{SELF\text{-}SIMILARITY}_j \\ + b_5 \times \mathrm{EXPERTISE}_i \\ + b_6 \times \mathrm{SYMMETRY}_j \times \mathrm{EXPERTISE}_i \\ + b_7 \times \mathrm{SIMPLICITY}_j \times \mathrm{EXPERTISE}_i \\ + b_8 \times \mathrm{CONTRAST}_j \times \mathrm{EXPERTISE}_i \\ + b_9 \times \mathrm{SELF\text{-}SIMILARITY}_j \times \mathrm{EXPERTISE}_i \\ + u_{0i} + u_{0j} + \varepsilon_{ij}.\end{aligned} \tag{2}$$

[2] In an earlier version of this article, we used grayscale versions of the pictures to calculate symmetry, contrast, and self-similarity. The scores based on the grayscale versions are highly correlated with the scores based on the colored pictures (symmetry: $r = .947$; contrast: $r = .897$; self-similarity: $r = .994$; all $p < .001$).

For all models, we checked possible multicollinearity between the predictors by estimating variance inflation factors (VIF). All VIF values were clearly under the critical value of 10 (all VIFs $\leq$ 2.128).

Results

We first examine the intercorrelations of the four aesthetic measures to determine whether they are independent (considering three different versions of the simplicity measure: ZIP/deflate, JPG, and GIF). The corresponding correlation coefficients show that all four measures are only slightly correlated (see Table 1). Exceptions are the correlation between symmetry and simplicity (r = .257 to .349, $p < .001$, depending on the simplicity algorithm) and self-similarity and simplicity when simplicity is measured using JPG or GIF ($r = -.379$ to $-.543$, $p < .001$). The three simplicity measures are all substantially but not extremely correlated (r = .659 to .764, $p < .001$). Further, all measures are associated with aesthetic liking (ratings aggregated per picture for this analysis): symmetry (r = .197, $p < .001$), contrast (r = .174, $p < .001$), and self-similarity (r = .244, $p < .001$) are positively correlated to aesthetic liking, and simplicity is negatively correlated (or not at all, depending on the image compression algorithm; ZIP/deflate: $r = -.070$, $p = .083$; JPG: $r = -.162$, $p < .001$; GIF: $r = .025$, $p = .527$).

Table 2 shows the results of the three LMMs described by Formula (1). For the model in which ZIP simplicity was used, we find that symmetry ($b = .876$, $t = 3.22$, $p = .0013$), contrast ($b = .942$, $t = 3.75$, $p < .001$), and self-similarity ($b = 1.360$, $t = 5.46$, $p < .001$) are positively related to liking. Simplicity, in contrast, is negatively connected to liking ($b = -.512$, $t = -1.98$, $p = .048$), indicating that more complex pictures result in higher aesthetic liking. The effects remain essentially the same when using JPG compression to measure simplicity, with the exception that the effect of simplicity on liking is not significant ($p = .408$). When the GIF compression is used, the effect of symmetry on liking is only marginally significant ($p = .063$) and the effect of simplicity on liking is positive but insignificant ($p = .104$). All three models explain a substantive amount of variance[3] in the participants' liking judgments (multiple correlation between fitted and observed values [R^2] for all three models = .318).

Including art expertise and its interactions with the objective measures as additional predictors in the models (Formula 2) does not change the direction or the magnitude of the main effects compared with the models without art expertise, nor does it increase the explained variance (see Appendix F). Art expertise itself contributes positively to aesthetic liking ($b = 2.424$, $t = 5.55$, $p < .001$ in all models). All interaction terms, however, are not significant (see Figure 5).

Discussion

Study 1 examined the relations between four objective measures of visual stimulus characteristics and aesthetic liking based on 620 images of digital abstract artworks. We further systematically compared different image compression algorithms to measure visual simplicity. The results point to significant relationships between the four objective measures and aesthetic liking, although being rather small in their magnitude. Likewise, we found only modest correlations among the measures, suggesting that they can serve as independent predictors of aesthetic liking (even the slightly higher correlation between symmetry and simplicity is far from posing any multicollinearity issues). Additionally, we found a negative correlation between simplicity and self-similarity for JPG and GIF simplicity, which is in line with previous research (Joye et al., 2016 for JPG complexity). Moreover, the different simplicity measures are all substantially correlated, and the correlation between JPG complexity and GIF complexity is almost exactly the same as in prior studies (r = .76 this study vs. r = .75 in Forsythe et al., 2011, p. 56, Table 1, "abstract artistic").

When analyzing the link between the measures and aesthetic liking (based on bivariate correlations and LMMs), we find, in accordance with the predictions of a fluency account of aesthetic liking (Reber, Schwarz et al., 2004; Winkielman, Halberstadt, Fazendeiro, & Catty, 2006) and research on self-similarity (Joye et al., 2016; Zeki, 1999), that symmetry, contrast, and self-similarity are positively associated with aesthetic liking. In contrast, simplicity is negatively associated with aesthetic liking when using ZIP compression or JPG compression (correlation analysis only), which replicates prior empirical findings on visual complexity in the domain of product design (Landwehr et al., 2011). Conversely, GIF simplicity does not yield significant results. This finding is in accordance with Marin and Leder (2013) who found in their study on IAPS pictures that the GIF format is only a weak indicator of subjective complexity evaluations (Experiment 1), and that GIF and JPG are not correlated to subjective complexity when it comes to representational paintings (Experiment 2).[4]

The pattern of results for the different simplicity measures suggests two implications. First, the image compression algorithms cannot be used interchangeably to measure simplicity because the correlations with liking and other measures can differ fundamentally depending on the compression algorithm (e.g., r(JPG, self-similarity) = $-.543$ vs. r(ZIP, self-similarity) = $-.052$). In the present research context (analyzing colored digital abstract artworks), we find that the ZIP/deflate image compression algorithm produces the most consistent pattern of results (with regard to the different employed statistical analyses). Given these findings and the above-mentioned problems with the GIF and JPG file formats to measure simplicity (Marin & Leder, 2013), we recommend using ZIP/deflate compression instead of JPG or GIF for future research in similar research settings.

Second, the negative relationship between ZIP simplicity and aesthetic liking seems to contradict fluency theory. However, the result corroborates prior research that found positive effects of complexity (Forsythe et al., 2011; Landwehr et al., 2011; Marin & Leder, 2013). Recent developments in fluency theory suggest that this can be explained from a dual process perspective (Graf & Landwehr, 2015), according to which complexity would activate controlled instead of automatic processing. Under controlled processing, people aesthetically prefer stimuli that are low in fluency

[3] Including all two-way interaction terms does not improve the explanatory power of the model substantially ($\Delta R^2 < .001$), nor does including all possible interaction terms ($\Delta R^2 < .001$).

[4] For completeness, we additionally tested the PNG file format as in Marin and Leder (2013). We find that PNG and JPG scores are highly correlated ($r = .972$, $p < .001$) and produce almost identical results in all analyses.

Table 1
Means, Standard Deviations, and Correlations With Confidence Intervals of the Variables Used in Study 1

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. Liking	45.718	6.243							
2. Fluency	56.088	8.733	.429*** [.362, .491]						
3. Simplicity (ZIP)	.164	.079	−.070+ [−.148, .0092]	.343*** [.272, .411]					
4. Simplicity (JPG)	.849	.028	−.162*** [−.238, −.084]	.419*** [.352, .482]	.737*** [.699, .771]				
5. Simplicity (GIF)	.744	.030	.025 [−.053, .104]	.428*** [.362, .490]	.659*** [.612, .702]	.764*** [.729, .795]			
6. Symmetry	.262	.148	.197*** [.120, .272]	.300*** [.226, .370]	.340*** [.268, .408]	.257*** [.182, .329]	.349*** [.278, .417]		
7. Contrast	.203	.033	.174*** [.097, .249]	.013 [−.066, .091]	−.168*** [−.244, −.091]	−.194*** [−.269, −.117]	.211*** [.135, .285]	.189*** [.112, .264]	
8. Self-similarity	−.945	.332	.244*** [.169, .317]	−.100* [−.177, −.021]	−.052 [−.130, .027]	−.543*** [−.597, −.486]	−.379*** [−.445, −.310]	.166*** [.088, .241]	−.093* [−.171, −.015]

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Because participants rated either liking or fluency of the pictures, the ratings of liking and fluency were aggregated per picture for this analysis. Values in square brackets indicate the 95% confidence interval for each correlation. All $n = 620$.
+ $p < .10$. * $p < .05$. *** $p < .001$.

Table 2
Linear Mixed Models of Study 1 With Aesthetic Liking as the Dependent Variable and Different Compression Algorithms for Simplicity

	ZIP simplicity		JPG simplicity		GIF simplicity	
	Estimate [95% CI]	β [95% CI]	Estimate [95% CI]	β [95% CI]	Estimate [95% CI]	β [95% CI]
Fixed effects						
(Intercept)	45.713*** [44.754, 46.672]		45.713*** [44.753, 46.673]		45.713*** [44.753, 46.672]	
Simplicity	−.512* [−1.017, −.0063]	−.018 [−.035, −.00022]	−.279 [−.941, .382]	−.010 [−.033, .013]	.464 [−.094, 1.021]	.016 [−.0033, .035]
Symmetry	.876** [.343, 1.409]	.030 [.012, .049]	.794** [.228, 1.361]	.028 [.0079, .047]	.511 [−.026, 1.048]	.018 [−.00090, .036]
Contrast	.942*** [.449, 1.435]	.033 [.016, .050]	.987*** [.461, 1.513]	.034 [.016, .053]	1.050*** [.574, 1.525]	.036 [.020, .053]
Self-similarity	1.360*** [.872, 1.848]	.047 [.030, .064]	1.264*** [.616, 1.911]	.044 [.021, .067]	1.660*** [1.115, 2.205]	.058 [.039, .077]
Random effects						
N_{id}	1,163		1,163		1,163	
N_{pic}	620		620		620	
ICC_{id}	.264		.264		.264	
ICC_{pic}	.034		.034		.034	
Observations	69,778		69,778		69,778	
R^2/Ω_0^2	.318/.317		.318/.317		.318/.317	

Note. All models include random intercepts per participant (id) and picture (pic). All predictor variables were z-transformed prior to the analysis.
* $p < .05$. ** $p < .01$. *** $p < .001$.

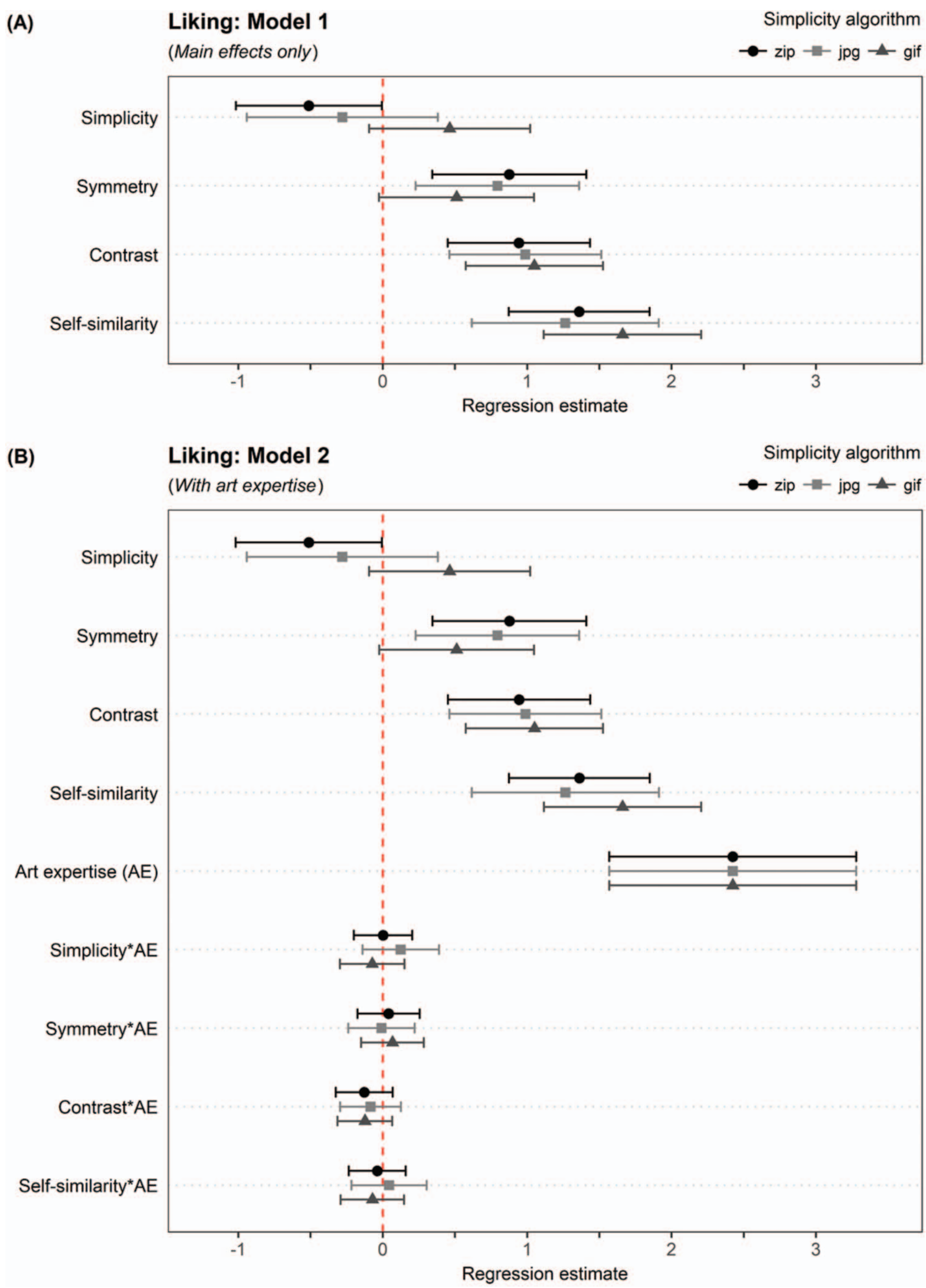

Figure 5. Results of all linear mixed models (LMMs) of Study 1 that predict aesthetic liking and comparison of the different simplicity algorithms. In Model 1 (part A), only the four aesthetic characteristics were included to predict aesthetic liking. In Model 2 (part B), art expertise was additionally included. Shown are the point-estimates from the LMMs with 95% confidence intervals. All models include a fixed intercept and crossed random intercepts per participant and picture. See the online article for the color version of this figure.

and challenge their processing. Therefore, complex stimuli are perceived as aesthetically more interesting than simple stimuli and hence are better liked. This explanation is also in line with other recent findings showing that both fluency and disfluency can be beneficial (Alter, 2013; Belke, Leder, & Carbon, 2015; Consoli, 2015).

In addition to the analyses reported in detail in the results section, we estimated two LMMs (identical to the models described above using ZIP simplicity) with processing fluency as the dependent variable (see Appendix G and Appendix H for full details). Based on fluency theory, we expected positive effects of all four visual characteristics. For symmetry and simplicity, we found the expected positive effect. However, for contrast, we found no effect, and for self-similarity, we found a negative effect. Thus, the pattern of results for directly predicting fluency is mixed with respect to the theoretical assumptions, which can be explained by two potential shortcomings of our empirical approach. On the one hand, our empirical approach may have been inadequate to reveal participants' processing experience. In particular, we do not know whether the objective visual characteristics reflected by our measures (e.g., a picture's objective symmetry) translate into corresponding subjective perceptions (e.g., the picture looks symmetrical). On the other hand, prior research on fluency effects suggests that the fluency experience needs to be salient to enter judgmental processes (Hansen & Wänke, 2013). Hence, the variance in the randomly selected subset of stimuli the participants rated could have been insufficient to trigger noticeable experiences of processing fluency. Study 2 aims to address these two empirical issues and to provide evidence that our measures can also be used to systematically select experimental stimuli that vary in one visual characteristic while keeping all other characteristics constant.

Study 2

To evaluate whether the proposed objective measures adequately represent the intended characteristics, we conducted an experiment with stimuli from the Abstract Digital Artworks Database described in Study 1 that varied systematically on only one of the four visual characteristics. The hypothesis was as follows: If the measures are valid measures of the four characteristics, then systematically selecting those pictures based on the proposed algorithms that are high (vs. low) in one of the characteristics should be equivalent to an experimental manipulation of the visual characteristic. Accordingly, we expect that subjective evaluations of the perceived visual characteristics follow the objective manipulations, which should be reflected in successful manipulation checks of the visual characteristics. Furthermore, we assess whether participants respond with elevated sensitivity in their aesthetic liking and processing fluency judgments when confronted with experimentally selected stimuli from the extreme ends of the distributions of the objective visual characteristics such that the salience of the fluency experience is experimentally increased.

Method

The key goal of Study 2 was to find experimental stimuli that are extreme on one target dimension but neutral (i.e., not manipulated) on all other dimensions based on the objective, algorithmic measures. For example, one might want to find pictures that are high or low only in symmetry and that are therefore "neutral" in all other characteristics. To this end, we first z-transformed the scores of the objective measures for ease of interpretation.[5] Next, we implemented two sequential steps for each of the visual characteristics. First, for every target characteristic, we built a subset of pictures that were neutral on all other visual characteristics such that all z-scores were within a range of ± 1 *SD* around the mean. Second, we selected the three pictures with the highest scores and the three pictures with the lowest scores on the target characteristic within this subset of pictures (see Appendix I for the full stimulus set). The resulting 24 pictures[6] (4 characteristics $\times$ 3 highest and 3 lowest z-scores) constituted the stimulus material for Study 2.

Participants and procedure. We conducted Study 2 online and recruited a sample of 242 participants (49.2% female; $M_{\text{age}} = 36.1$, $SD_{\text{age}} = 12.2$) on Amazon MTurk. Participation was financially compensated, and all steps of the experiment were self-paced. We randomly assigned participants (between-subjects) to one of the visual characteristics (symmetry [$n = 59$] vs. simplicity [$n = 61$] vs. contrast [$n = 60$] vs. self-similarity [$n = 62$]). The levels of the respective characteristic (high vs. low) were manipulated within subjects in each of the four groups. Because we used three operationalizations per manipulation level, the participants subsequently rated six stimuli (three stimuli high and three stimuli low on the target characteristic) first with respect to aesthetic liking, then on a manipulation check, and finally with respect to subjective fluency, each time in a random order. All evaluations were made with one image per page.

Measures. Liking and fluency were measured identically to Study 1. The questions pertaining to the manipulation checks were as follows (answer format: horizontal slider with 100 continuous increments from *not at all* to *very much*, except as noted otherwise):

- Symmetry: *How symmetrical do you perceive this picture to be?* (*i.e., Does the left side of the picture look like the mirror image of the right side?*)
- Simplicity: *How complex do you perceive this picture to be?* (*i.e., Does the picture contain fine-grained varying elements?*; reverse coded)
- Contrast: *How rich in contrast do you perceive this picture to be?* (*i.e., Does the picture contain sharp edges instead of smooth transitions?*)
- Self-similarity: *How many fine, repeating details do you perceive this picture to have?* (*i.e., Does the picture contain repeating shapes or elements?*; ranging from *absolutely none* to *a great many*).

As in Study 1, we further asked participants to state their art expertise and to provide sociodemographic information at the end of the experiment.

Analysis. We analyzed the data by estimating 12 LMMs using the lme4 package (Bates, Mächler, et al., 2015), one for aesthetic liking, one for processing fluency, and one for the manipulation check, repeatedly for each of the four dimensions. In each model, the manipulation (high vs. low on the target characteristic) was included as an effect-coded predictor. Again, we used the lmerTest library (Kuznetsova et al., 2016) for Satterthwaite's approximated significance testing. Because of the repeated-measures structure of the data, we included a random intercept per participant in the

[5] The scores are based on a previous version of the measures that used grayscale instead of color images (please note that the scores are highly correlated; see Footnote 2). Furthermore, in a previous version of this article (i.e., at the time we ran the experiment), we included visual typicality as a visual characteristic (for details about the measurement of visual typicality, see Mayer & Landwehr, 2018). Therefore, the stimuli for the experiment were selected based on the following five dimensions: simplicity (ZIP), symmetry, contrast, self-similarity, and typicality.

[6] As described in the previous footnote, the actual experiment included a fifth visual dimension (visual typicality). Thus, in the experiment, we had six more pictures that were evaluated by 60 additional participants. However, as the assignment to one of the visual dimensions was manipulated between subjects, only the results for the remaining four dimensions are reported in this article.

models. The models had the following general form for participants i and pictures j with b indicating fixed effects, u indicating random effects, and ε indicating the error term:

$$DV_{ij} = b_0 + b_1 \times \text{MANIPULATION}_j + u_{0i} + \varepsilon_{ij}. \quad (3)$$

DV_{ij} was liking, fluency, or the manipulation check. We also ran the same models including a participant's art expertise (z-transformed) as a control variable (main effect and interaction):

$$DV_{ij} = b_0 + b_1 \times \text{MANIPULATION}_j + b_2 \times \text{EXPERTISE}_i + b_3 \times \text{MANIPULATION}_j \times \text{EXPERTISE}_i + u_{0i} + \varepsilon_{ij}. \quad (4)$$

Results

Figure 6 summarizes the results of the basic models as described by Equation (3), and Table 3 provides a detailed overview of all results. For all characteristics, the experimental manipulation was successful in the intended direction (see Table 3, rows "MC"). Regarding aesthetic liking, most results were as hypothesized: pictures that were high in either contrast or self-similarity resulted, as expected, in higher liking ratings (contrast: $b = 2.467$, $t = 2.21$, $p = .028$; self-similarity: $b = 5.376$, $t = 4.59$, $p < .001$). Pictures that were high in simplicity had, on average, significantly lower liking values ($b = -3.598$, $t = -2.84$, $p = .005$). Symmetry was not clearly associated with liking in the basic model ($p = .261$). Including art expertise as a predictor, however, revealed a significant negative interaction between the symmetry manipulation and art expertise ($b = -2.469$, $t = -1.99$, $p = .048$), indicating that participants low in art expertise preferred pictures that were high in symmetry and vice versa.

The results for processing fluency were mainly in line with our conceptual framework (see Table 3, rows "Flu"). The manipulations of simplicity, symmetry, and contrast had the expected positive effects on fluency (simplicity: $b = 5.384$, $t = 4.47$, $p < .001$; symmetry: $b = 2.773$, $t = 2.40$, $p = .017$; contrast: $b = 2.475$, $t = 2.38$, $p = .018$). Self-similarity, however, was not clearly associated with processing fluency ($p = .264$).

Discussion

Study 2 sought to examine whether our measures validly capture the intended characteristics of simplicity, symmetry, contrast, and self-similarity and whether the inconclusive results in Study 1 with respect to processing fluency can be clarified when salient manipulations of the visual characteristics are used. The results of the manipulation checks affirm that the experimental manipulations were successful by showing that objective visual characteristics translate into corresponding subjective perceptions. Hence, pictures that are selected based on the proposed measures are suitable as experimental stimuli that feature a systematic manipulation of a single visual characteristic.

Consistent with Study 1, contrast and self-similarity foster aesthetic liking in an experimental setting. Simplicity is negatively connected to liking, paralleling the findings of Study 1 and previous research (e.g., Landwehr et al., 2011). The effect of visual symmetry seems to depend on a person's art expertise. The interaction between symmetry and art expertise is negative for all three dependent variables (manipulation check, fluency, liking), suggesting that people low in art expertise prefer symmetrical pictures, whereas people high in art expertise prefer more challenging asymmetrical pictures. This pattern of results is in line with the dual process perspective on processing fluency presented in the discussion of Study 1 (Graf & Landwehr, 2015), assuming that art experts process art in a more controlled way than art novices.

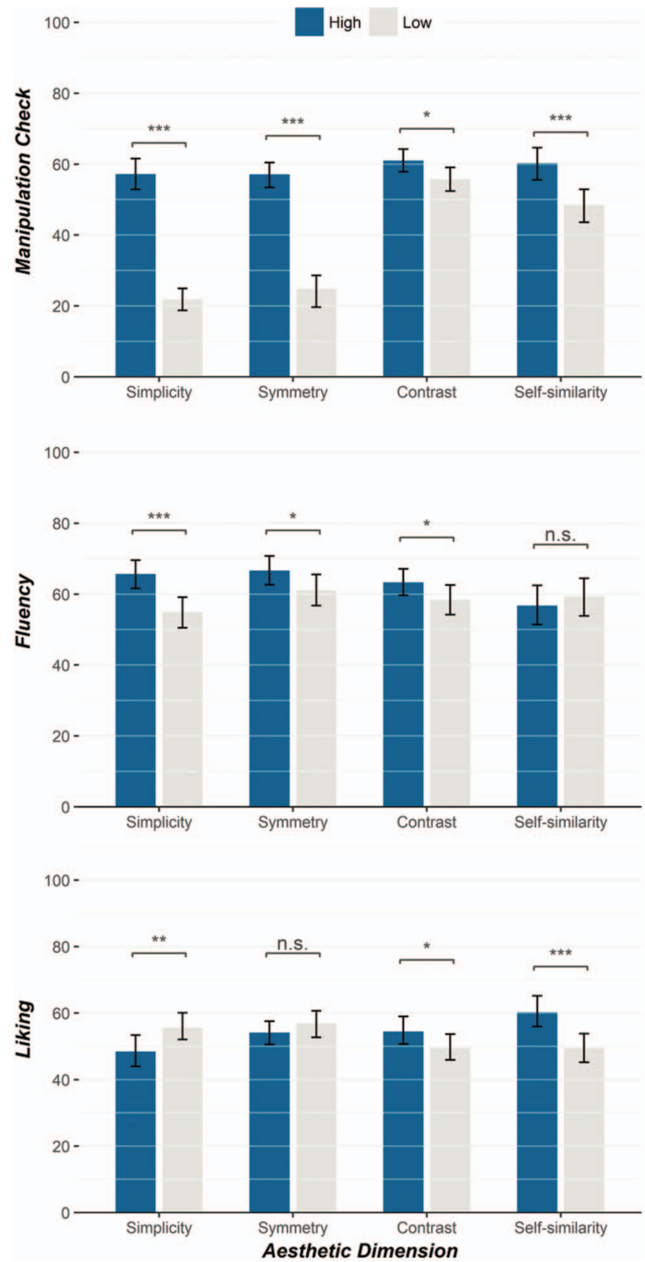

Figure 6. Summary of the basic models of Study 2. Participants were randomly assigned to one of the four aesthetic dimensions and rated six pictures (three low and three high on the dimension) with respect to aesthetic liking, processing fluency, and their subjective perception of the respective dimension. The bars represent the estimated means per condition (high/low) for each aesthetic dimension with bootstrapped 95% confidence intervals. * $p < .05$. ** $p < .01$. *** $p < .001$. n.s. = not significant. See the online article for the color version of this figure.

Considering processing fluency, Study 2 shows the predicted positive link to self-reported processing fluency for symmetry,

Table 3
Linear Mixed Models of Study 2

			Basic model				With art expertise (AE)			
			Estimate	95% CI	β	*p*	Estimate	95% CI	β	*p*
Simplicity (Simpl)	MC	Simpl	17.680	[14.653, 20.598]	.622	<.001	17.680	[14.737, 20.492]	.622	<.001
		Simpl × AE					−2.287	[−5.708, 1.222]	−.080	.036
	Flu	Simpl	5.384	[2.842, 7.978]	.198	<.001	5.384	[2.865, 7.855]	.198	<.001
		Simpl × AE					−1.852	[−4.255, .039]	−.068	.125
	Lik	Simpl	−3.598	[−6.549, −.847]	−.129	.005	−3.713	[−6.546, −.836]	−.133	.004
		Simpl × AE					1.275	[−1.458, 3.800]	.046	.315
Symmetry (Sym)	MC	Sym	16.150	[14.011, 18.709]	.476	<.001	16.438	[14.155, 18.624]	.484	<.001
		Sym × AE					−3.258	[−5.673, −.625]	−.096	.025
	Flu	Sym	2.773	[.317, 5.357]	.105	.017	2.772	[.327, 5.387]	.105	.017
		Sym × AE					−2.367	[−4.715, −.097]	−.090	.041
	Lik	Sym	−1.381	[−3.475, .777]	−.052	.261	−1.350	[−3.482, .736]	−.051	.277
		Sym × AE					−2.469	[−4.525, −.714]	−.094	.048
Contrast (Contr)	MC	Contr	2.636	[.658, 4.65]	.104	.036	2.636	[.587, 4.672]	.104	.036
		Contr × AE					−.254	[−2.356, 1.711]	−.010	.840
	Flu	Contr	2.475	[.762, 4.21]	.098	.018	2.475	[.708, 4.203]	.098	.018
		Contr × AE					−.907	[−2.862, .691]	−.036	.384
	Lik	Contr	2.467	[.611, 4.447]	.092	.028	2.522	[.596, 4.481]	.094	.024
		Contr × AE					1.215	[−.750, 3.209]	.045	.277
Self-similarity (Self-sim)	MC	Self-sim	5.870	[3.075, 8.761]	.223	<.001	5.870	[3.192, 8.759]	.223	<.001
		Self-sim × AE					−2.334	[−5.149, .117]	−.088	.021
	Flu	Self-sim	−1.261	[−4.815, 2.427]	−.044	.264	−1.261	[−4.876, 2.46]	−.044	.264
		Self-sim × AE					−.492	[−3.210, 1.734]	−.017	.663
	Lik	Self-sim	5.376	[2.495, 8.441]	.197	<.001	5.376	[2.496, 8.413]	.197	<.001
		Self-sim × AE					−1.895	[−4.493, .303]	−.069	.110

Note. For each dependent variable within each aesthetic characteristic, two models were estimated: one only with the manipulation as predictor, one additionally including art expertise. MC = manipulation check; Flu = fluency; Lik = liking. All models include fixed intercepts and random intercepts per participant. The interaction models also include main effects for art expertise (not reported). Model fit by REML. Significance testing is based on Satterthwaite's approximation for the degrees of freedom. The confidence intervals (CI) are based on 5,000 bootstraps. Art expertise was z-transformed prior to analysis. Effect coding was used for the corresponding experimental factors in the models.

simplicity, and contrast. The nature of the relationship between self-similarity and fluency, however, cannot be clarified by Study 2. Study 1 indicates a negative relationship, and Study 2 indicates a null effect.

Study 3

Studies 1 and 2 consistently reveal that simplicity, contrast, self-similarity, and symmetry (moderated by art expertise in Study 2) significantly influence aesthetic liking. To further evaluate the generalizability of this finding, Study 3 investigated whether we find similar effects for a completely different set of stimuli. To this end, we analyzed whether our proposed measures would predict how often photos were viewed on the popular image hosting website Flickr.com. Prior research has confirmed that the duration of visual exploration is a consequence of aesthetic preference (Brieber, Nadal, Leder, & Rosenberg, 2014), which implies that the likelihood of clicking on a thumbnail image on Flickr.com to enable a deeper visual exploration should be related to aesthetic preference. Thus, instead of aesthetic liking, we used the number of views (i.e., clicks) as an indicator of aesthetic preference. Because the number of views certainly captures more aspects than just aesthetic liking, we expect weaker effects of the low-level image properties compared with the previous studies, which measured aesthetic preferences more directly. In contrast to the previous studies, we have no measure or proxy for processing fluency in this dataset.

Method

Flickr.com is a popular image hosting website where users can host personal photographs and share them publicly. In March 2013, Flickr reported that more than 3.5 million new images were uploaded every day from a total of 87 million registered members worldwide (Jeffries, 2013), resulting in more than 6 billion images hosted on Flickr.com in 2011 (Parfeni, 2011). Importantly, photos on Flickr.com can be searched for and viewed without having to sign up for an account. Moreover, Flickr provides an API (Application Programming Interface) that enables easy access to the image database (see https://www.flickr.com/services/api/).

Procedure. We used the "flickrr" library from the statistical software "R" (Hester, 2016; see https://github.com/jimhester/flickrr) to directly access the Flickr API from R. Specifically, we used the "flickr.photos.search" API command to search for photos with the text "landscape" on Flickr.com. We chose landscapes because landscape pictures are quite uniform in the depicted content and they usually trigger a spontaneous aesthetic impression. Moreover, self-similarity should be particularly present in pictures of natural scenes because repeating patterns characterize many natural objects such as clouds, trees, plants, and mountain ranges (Gouyet, 1996; Mandelbrot, 1982). The API command identifies all photos that contain the word "landscape" in the title, description, or tag. We used the "relevance" parameter to sort the results by relevance to the search term to mimic the website's default behavior when users search for a text string. In addition, we limited the number of results to the first 500 photos (i.e., the 500 most relevant photos) because this is the maximum value allowed by the API command.

Flickr provides each image in different resolutions. We extracted the URLs of all 500 images in the "small" resolution (i.e., width of 240 pixels). We chose to use this resolution because it is similar to the size of the images that users see on the search results page on the website (i.e., thumbnail-like images). Finally, we downloaded all 500 images using the "download.file()" command in R.

Measures. We measured the number of views for each photo using the "flickr.photos.getInfo" API command. Among other information, this command returns how often a photo has been viewed on the website. In addition, the command returns the date on which the photo was uploaded on the website.[7] Furthermore, we recorded the rank of a photo in the search result list. Finally, we applied our four objective measures to all 500 downloaded photos using ZIP compression for simplicity. Appendix J shows descriptive plots for all variables used in Study 3.

Analysis. We analyzed the data by estimating two OLS regressions predicting the number of views. However, because the number of views is heavily positively skewed, we log-transformed the number of views for the analyses. The first model (controls-only model) predicted log(views) of a photo *i* as a function of the rank in the search results and the time since the photo was uploaded in days:

$$\log(\text{VIEWS})_i = b_0 + b_1 \times \text{RANK}_i + b_2 \times \text{TIME}_i + \varepsilon_i. \quad (5)$$

The second model additionally included the four image properties as predictors (z-standardized prior to analysis):

$$\begin{aligned}\log(\text{VIEWS})_i = b_0 &+ b_1 \times \text{RANK}_i + b_2 \times \text{TIME}_i \\ &+ b_3 \times \text{SIMPLICITY\_ZIP}_i + b_4 \times \text{SYMMETRY}_i \\ &+ b_5 \times \text{CONTRAST}_i \\ &+ b_6 \times \text{SELF-SIMILARITY}_i + \varepsilon_i. \quad (6)\end{aligned}$$

Table 4 shows the descriptive statistics for all variables of the models. For both Models (5) and (6), we checked possible multicollinearity between the predictors by estimating variance inflation factors (VIF). All VIF values were clearly under the critical value of 10 (all VIFs $\leq$ 1.409).

Results

Table 5 shows the results of both regression models. For the controls-only model as described by Equation (5), we found, as expected, that the rank in the search results and the elapsed time since a photo's upload significantly influenced the (logged) number of views (rank: $b = -.0024$, $t = -22.24$, $p < .001$; time: $b = .00015$, $t = 7.85$, $p < .001$). The second model that additionally included the four image properties as predictors (see Equation 6) replicated these two effects. In addition, simplicity and self-similarity were significantly related to the logged number of views (simplicity: $b = .048$, $t = 2.82$, $p = .005$; self-similarity: $b = .036$, $t = 2.26$, $p = .024$), suggesting that simpler and more self-similar images were viewed more often. The coefficients for symmetry and contrast were in the expected direction but did not reach significance (symmetry: $b = .026$, $t = 1.44$, $p = .150$; contrast: $b = .022$, $t = 1.28$, $p = .202$). Importantly, including the four aesthetic measures in the model[8] significantly increased the explained variance in the logged number of views by approximately 2% ($R^2 = .568$ vs. $R^2 = .550$ in the controls-only model; $F(4, 493) = 5.081$, $p < .001$).

Discussion

The aim of Study 3 was to test the generalizability of our previous findings from Studies 1 and 2 that simplicity, symmetry, contrast, and self-similarity influence aesthetic preferences. To this end, we applied our four measures to a completely different dataset: photos uploaded on the image hosting website Flickr.com. In particular, we scraped 500 images of landscapes and recorded how often they were viewed on the website (i.e., clicked on after users saw a thumbnail preview of the image on a search result page). Thus, we used not only a different image database compared with Studies 1 and 2 but also a different indicator of aesthetic preferences.

As expected from Studies 1 and 2, the results showed that images high in self-similarity were viewed more often than images with lower self-similarity. In contrast to Studies 1 and 2, however, simplicity had a positive effect on the number of views on Flickr. Thus, it seems that whereas images of abstract art are more likable if they are more complex (at least for our dataset), images of natural scenes (in this case, landscapes) benefit from simplicity. When considered from a dual-process perspective on processing fluency (Graf & Landwehr, 2015), these results suggest that abstract art is processed on a controlled processing level and triggers aesthetic interest, whereas landscape pictures are processed on an automatic processing level and trigger aesthetic pleasure. For symmetry and contrast, Study 3 did not reveal significant results,[9] although the direction of the effects was consistent with Studies 1 and 2. This finding indicates that the effects of symmetry and contrast are rather small for photos of landscapes and that the number of views on the picture level is obviously a more "messy" dependent variable than aesthetic liking on the individual level. Therefore, we recommend that future studies may benefit from larger sample sizes (i.e., more images).

[7] In particular, the Flickr API returns the date in the POSIX format (i.e., the number of elapsed seconds since 00:00:00 UTC, January 1, 1970). The mean upload date in our sample was October 1, 2013. To allow for easier interpretation, we transformed the values so that they indicate the number of days elapsed from the upload date to the time we downloaded the images (June 29, 2017).

[8] A model that includes all two-way interaction terms for the four aesthetic measures yields no significant interaction effects, and the pattern of results for the main effects is almost the same. This two-way interaction-model, however, does not increase the explanatory power compared to the more parsimonious main-effects model, $\Delta R^2 = .004$; $F(6, 487) = 0.693$, $p = .656$. Furthermore, a model with all possible interaction effects between the four aesthetic measures does not significantly improve the explanatory power of the model, $\Delta R^2 = .008$; $F(11, 482) = 0.837$, $p = .603$.

[9] We additionally analyzed the data with two alternative statistical models for count data: Poisson regression and negative binomial regression. Using a Poisson regression model, the effects of all four visual characteristics were significantly positive (all $p < .001$). However, using a negative binomial regression model, the results were the same as those reported in the results section of Study 3 (i.e., significant positive effects of simplicity and self-similarity but insignificant effects of symmetry and contrast).

Table 4
Means, Standard Deviations, and Correlations With Confidence Intervals of the Variables Used in Study 3

Variable	*M*	*SD*	1	2	3	4	5	6
1. Views (log10)	4.548	.516						
2. Rank	250.50	144.48	−.703*** [−.745, −.656]					
3. Time	1365.94	797.47	.320*** [.239, .397]	−.122** [−.207, −.034]				
4. Simplicity	.305	.147	.135** [.048, .220]	−.034 [−.122, .054]	.064 [−.024, .151]			
5. Symmetry	.651	.206	.135** [.048, .220]	−.050 [−.137, .038]	.060 [−.027, .147]	.378*** [.300, .450]		
6. Contrast	.233	.049	.059 [−.029, .146]	.005 [−.083, .092]	.037 [−.051, .125]	.045 [−.043, .132]	.394*** [.317, .465]	
7. Self-similarity	−.349	.222	.064 [−.023, .151]	−.087+ [−.174, .00032]	−.109* [−.195, −.021]	−.225*** [−.306, −.140]	−.201*** [−.284, −.116]	−.180*** [−.263, −.093]

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. The number of views is log-transformed. Time is the number of days elapsed since the picture was uploaded on Flickr.com. All $n = 500$.
+ $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

General Discussion

One of the simplest human judgments is the answer to the question "How much do you like what you currently see?" Nevertheless, identifying the objective visual stimulus characteristics that determine such a liking judgment is a difficult scientific question with no convincing answers thus far. Although there may be many explanations for why humans like what they see (e.g., McManus & Stöver, 2014), our research aimed to answer this question by examining low-level image properties based on processing fluency theory. To this end, we presented a coherent set of four fluency-based visual antecedents of aesthetic preferences that can be algorithmically extracted from a given visual stimulus.

Over the course of three studies, we examined the validity and empirical usefulness of these four visual characteristics. For this purpose, we built a database of abstract digital artworks consisting of 620 standardized pictures that were evaluated with regard to aesthetic liking and processing fluency by more than 2,000 participants. In Study 1, we examined the relative importance of the four measures by considering all four conjointly. Specifically, participants had to rate random subsets of the artworks; thus, they were faced with random variation in the four characteristics without any characteristic being particular salient. By including all four characteristics in one statistical model, we were able to quantify the relative importance and the unique contribution of each of the four visual characteristics while controlling the concurrent effect of the other characteristics. We found that even when controlling for the other characteristics, all four measures contributed independently to aesthetic liking. With respect to relative importance, we found that the most important determinants of aesthetic liking for our stimulus set of abstract artworks were, in descending order, self-similarity, contrast, symmetry, and complexity (i.e., simplicity had a negative effect on liking).

We additionally investigated whether different image compression algorithms for an objective simplicity measure could be used interchangeably. Although the scores on the ZIP/deflate, JPG, and GIF-based simplicity measures were substantially correlated, our results suggest that ZIP/deflate works best when controlling for other low-level image properties. Thus, we recommend using the ZIP/deflate algorithm for future research on low-level visual determinants of aesthetics.

Study 2 adopted an experimental perspective and examined isolated effects of the four visual characteristics featuring a maximization of primary variance. The participants were confronted with preselected stimuli that varied on only one of the four characteristics, with half the stimuli being extremely low and the other half being extremely high on the visual characteristic. Thus, in contrast to Study 1, the experimental variation was very salient in Study 2. Using this setup, we found that the subjective perceptions of the four visual characteristics corresponded to the intended measurement characteristics of the objective measures in a manipulation check. Hence, the measures seem to validly capture what they were meant to capture. Furthermore, in this salient experimental setup, the positive effects of contrast and self-similarity and the negative effect of simplicity of Study 1 were replicated. However, the positive effect of symmetry was only replicated for participants low in art expertise. One explanation for this finding is that art expertise selectively changes the type of processing from automatic to controlled processing (Graf & Landwehr, 2015).

Table 5
OLS Regression Models of Study 3

	Controls-only		With aesthetic measures	
	Estimate [95% CI]	β [95% CI]	Estimate [95% CI]	β [95% CI]
(Intercept)	4.941*** [4.856, 5.026]		4.932*** [4.848, 5.016]	
Rank	−.0024*** [−.0026, −.0022]	−.674 [−.734, −.615]	−.0024*** [−.0026, −.0022]	−.663 [−.722, −.604]
Time	.00015*** [.00012, .00019]	.238 [.179, .297]	.00015*** [.00011, .00019]	.237 [.178, .295]
Simplicity			.048** [.014, .081]	.092 [.028, .157]
Symmetry			.026 [−.0095, .062]	.051 [−.018, .120]
Contrast			.022 [−.012, .055]	.042 [−.022, .106]
Self-similarity			.036* [.0048, .068]	.071 [.0094, .132]
Observations	500		500	
R^2/adj. R^2	.550/.548		.568/.563	
Incremental F-test			$F(4, 493) = 5.081^{***}$	

Note. For both models, the logged number of views on Flickr served as the dependent variable. The scores on symmetry, simplicity, contrast, and self-similarity were z-standardized prior to the analysis. Time is the number of days elapsed since the picture was uploaded on Flickr.com.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Therefore, the art experts may have contemplated the visual characteristics instead of following their gut-level fluency preference.

The pattern of results for subjectively experienced processing fluency across the two studies does not provide a coherent picture. Whereas symmetry and simplicity consistently increase processing fluency as expected, the effects of contrast and self-similarity are not consistent across the studies. Although we used the processing fluency framework to guide the selection of relevant visual characteristics, our empirical evidence indicates that more research is needed to link all visual characteristics to the experience of processing fluency. This may require objective measures of processing fluency (e.g., response times, neuronal activity) to also capture nonconscious fluency experiences. At the same time, it may require more complex theoretical models of the link between processing fluency and aesthetic liking that account for conditions that shift preferences from fluency to disfluency and vice versa (e.g., Armstrong & Detweiler-Bedell, 2008; Belke, Leder, Strobach, & Carbon, 2010; Carbon & Leder, 2005; Graf & Landwehr, 2015; Muth & Carbon, 2013).

In a third study, we aimed to test the generalizability of our findings. To this end, we investigated whether the prediction of how often a picture would be viewed on an image hosting platform could be improved by incorporating the four low-level image properties in a statistical regression model. Although only self-similarity and simplicity have significant effects, including the four objective measures significantly improves the explained variance of the model. For this dataset, however, simplicity has a positive effect, which is consistent with processing fluency theory but contradicts the findings from Studies 1 and 2. This discrepancy can be explained by a dual-process perspective on processing fluency (Graf & Landwehr, 2015). In particular, this framework suggests that abstract art triggers a need for cognitive enrichment, which makes people process stimuli on a controlled level. On this processing level, people initially prefer a low level of fluency (i.e., visual complexity) that may shape an aesthetic liking judgment through aesthetic interest. In contrast, landscape photographs do not trigger a need for cognitive enrichment. Therefore, they are processed on an automatic level. At this level, people prefer a high level of fluency (i.e., visual simplicity), which may feed into an aesthetic liking judgment through an experience of aesthetic pleasure. These merely theoretical explanations based on the *pleasure-interest model of aesthetic liking* (Graf & Landwehr, 2015) should be put to a rigorous empirical test by future research.

An alternative explanation for the inconsistent findings of Study 3 could be that human beings have a lot more experience with landscapes compared with abstract art. Therefore, pictures of landscapes might trigger such a high base level of fluency that differences in fluency-related, low-level image properties might have a reduced effect.[10] Thus, follow-up studies may want to examine the relationship between simplicity and aesthetic liking in stimulus categories over and above the ones we used in our studies (e.g., representational art, product design, architecture) to clarify when and why simplicity or complexity is preferred. Future studies are also advised to examine the relationship between the other three fluency-related measures and aesthetic liking in different contexts. Likewise, because the four measures explain only a mediocre share of variance in participants' aesthetic liking judgments, future research should examine whether there are additional low-level visual characteristics that might further improve the prediction of aesthetic liking based on mere visual stimulus characteristics. On a related note, we considered only vertical symmetry as the perceptually most dominant type of symmetry and ignored other types of symmetry (e.g., horizontal, rotational, or local symmetries). Thus, it may be interesting to examine how the prediction of liking judgments can be improved when other types of symmetry are considered as well.

A final inspiration for future research comes from previous research on aesthetic preferences for rectangles that suggests weak population effects but strong and consistent interindividual differences (McManus, Cook, & Hunt, 2010). Our results on visually richer stimuli show the opposite pattern: strong and consistent population effects, which remain unchanged by interindividual difference variables (we tested art expertise, age, and gender). Thus, future research may want to examine whether other interindividual difference variables moderate the effects of our four

[10] We thank an anonymous reviewer for this suggestion.

measures and whether aesthetic preferences for plain geometric shapes depend to a greater extent on idiosyncratic aesthetic preferences than visually richer aesthetic stimuli do.

To conclude, our findings suggest that visual antecedents of aesthetics can be quantified with four stimulus-driven, algorithmically measurable characteristics on the basis of the processing fluency framework. We built a database of 620 pictures that can be used in future studies to develop and benchmark more image statistics and algorithmic measures related to aesthetic preferences. Furthermore, the database can serve as a convenient pool of experimental stimuli that systematically vary in one specific characteristic while keeping all other characteristics constant. By *measuring what is measurable and making measurable what was not measurable before*, we hope to contribute to future discoveries of empirical aesthetic phenomena and to the advancement of theories on the mechanisms underlying aesthetic judgments.

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(*Appendices follow*)

Appendix A

Analysis of Fourier Power Spectra

We measured visual self-similarity with the $1/f^2$ Fourier power spectrum by analyzing the distribution of the spectral power of an image as a function of the spatial frequencies (Graham & Field, 2007; Redies et al., 2007). Image analysis was performed using the statistical programming language "R." We first transformed each image into the frequency domain using Fast Fourier Transform. Then, for each frequency, the rotational average of the power spectrum was computed and plotted against frequency on a log-log plane. We subsequently fit an OLS regression to the log-log power spectrum and analyzed the slope of the regression (Figure A1). A slope near -2 indicates fractal-like properties. The visual self-similarity measure was computed as self-similarity = abs(slope + 2) $*$ (-1). Note that only the frequency range between 10 and 256 cycles per image was used for interpolation (Redies et al., 2007). However, the results do not change if the full range is used.

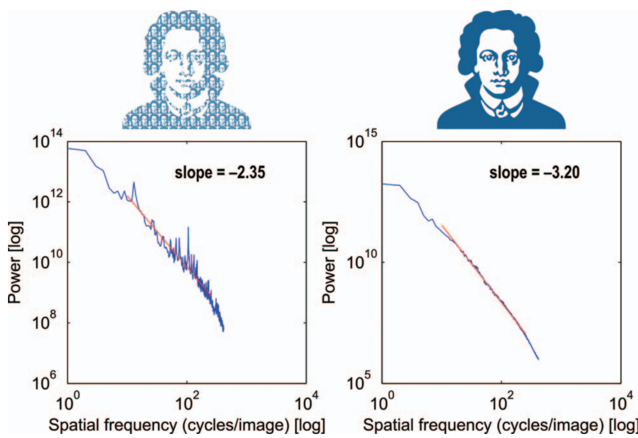


Figure A1. Fourier power spectra of two different images. The rotational average of the power spectrum is plotted against frequency on a log-log plane. The red line indicates the slope of an OLS regression fit to the data. A slope near -2 indicates fractal-like properties. See the online article for the color version of this figure.

(*Appendices continue*)

Appendix B

ZIP Compression Algorithm Bias

Previous studies used the ZIP file format with the deflate compression algorithm as a measure of visual simplicity. However, this approach does not depict horizontal and vertical redundancies equally, leading to a biased measure of visual simplicity. Figure B1 shows an image with an uncompressed file size of 750 KB, in original orientation and rotated by 90 degrees. Compressing each image with the ZIP/deflate algorithm results in quite different file sizes.

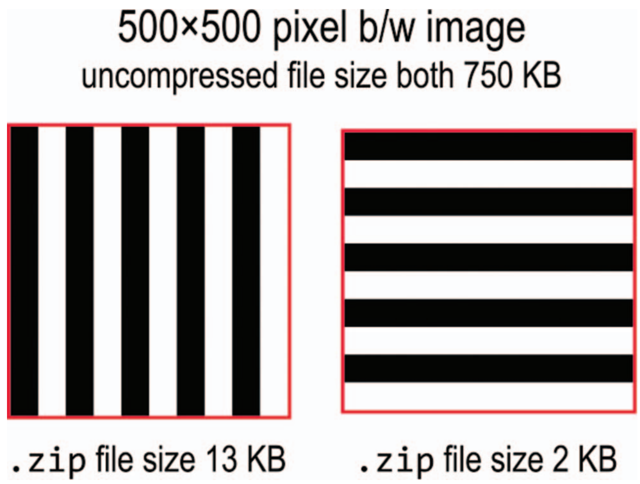


Figure B1. Illustration of the ZIP/deflate compression algorithm bias as a measure of visual simplicity. See the online article for the color version of this figure.

(*Appendices continue*)

Appendix C

Example for Symmetry Aggregation Using the Luma Color Coding System

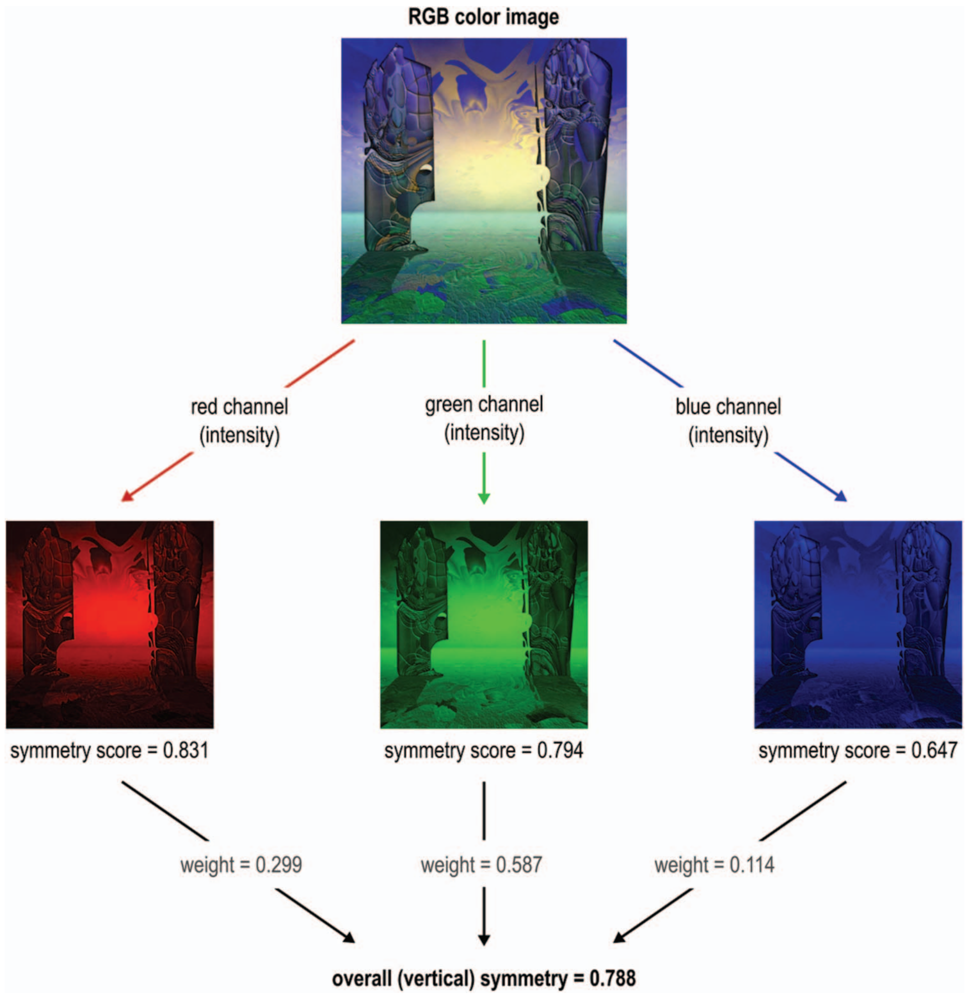


Figure C1. Illustration of measuring symmetry by analyzing the three color channels separately and then aggregating the scores according to Luma color coding. Sample picture taken from http://sanbase.com/gallery.html © 2016 San Base. All rights reserved. Used with permission. See the online article for the color version of this figure.

(*Appendices continue*)

Appendix D

Details About the Abstract Digital Artworks Database

All pictures used in the database are from http://sanbase.com/gallery.html. At this URL, the artist San Base provides 1,000 computer-generated biomorphic paintings in the style of digital abstract surrealism in the JPG file format with a resolution of 1,200 × 900 pixels. To build the Abstract Digital Artworks Database for our studies, we first manually downloaded all available images in May and June 2013 (see Figure D1 for examples). Next, we selected only images that had the artist's watermark in the rightmost and bottommost position of the picture because we wanted to crop the watermarks in the next step (see, for example, http://sanbase.com/image.php?img=download/1000/a444.1.jpg vs. http://sanbase.com/image.php?img=download/1000/ex2.jpg). This process resulted in 860 pictures. The next step included cropping the pictures so that the artist's watermark was no longer part of the picture. We chose to do this because we wanted to avoid any distraction of the participants when rating the pictures and to avoid any bias for the objective measures. We additionally chose to crop the pictures to a square dimension because this is a requirement for the Fourier analysis (see the description of the measurement of self-similarity in the main text). Thus, we cropped all 860 pictures to a resolution of 840 × 840 pixels (cropping equally from all sides, see Figure D2). We then downsampled all pictures to a resolution of 512 × 512 pixels and saved them as uncompressed bitmap files (BMP) to avoid artifacts in any analysis due to compression.

Of the 860 pictures, most can be described as images of different abstract forms, shapes, and patterns, partially with a foreground and background. However, some of the images depict visual objects in which participants could recognize meaning (e.g., trees, mountains, or eyes); other images comprise a composition of different subimages; and a few others stand out due to their striking black or white background. Therefore, a set of three independent raters categorized all 860 images into six different groups: (a) images with meaning, (b) black background, (c) composition, (d) shapes, (e) foreground and background, and (f) other. Overall, the three raters agreed on 65.7% of the images (Fleiss'

Figure D1. Sample pictures from the database. All pictures are from http://sanbase.com/gallery.html © 2016 San Base. All rights reserved. Used with permission. See the online article for the color version of this figure.

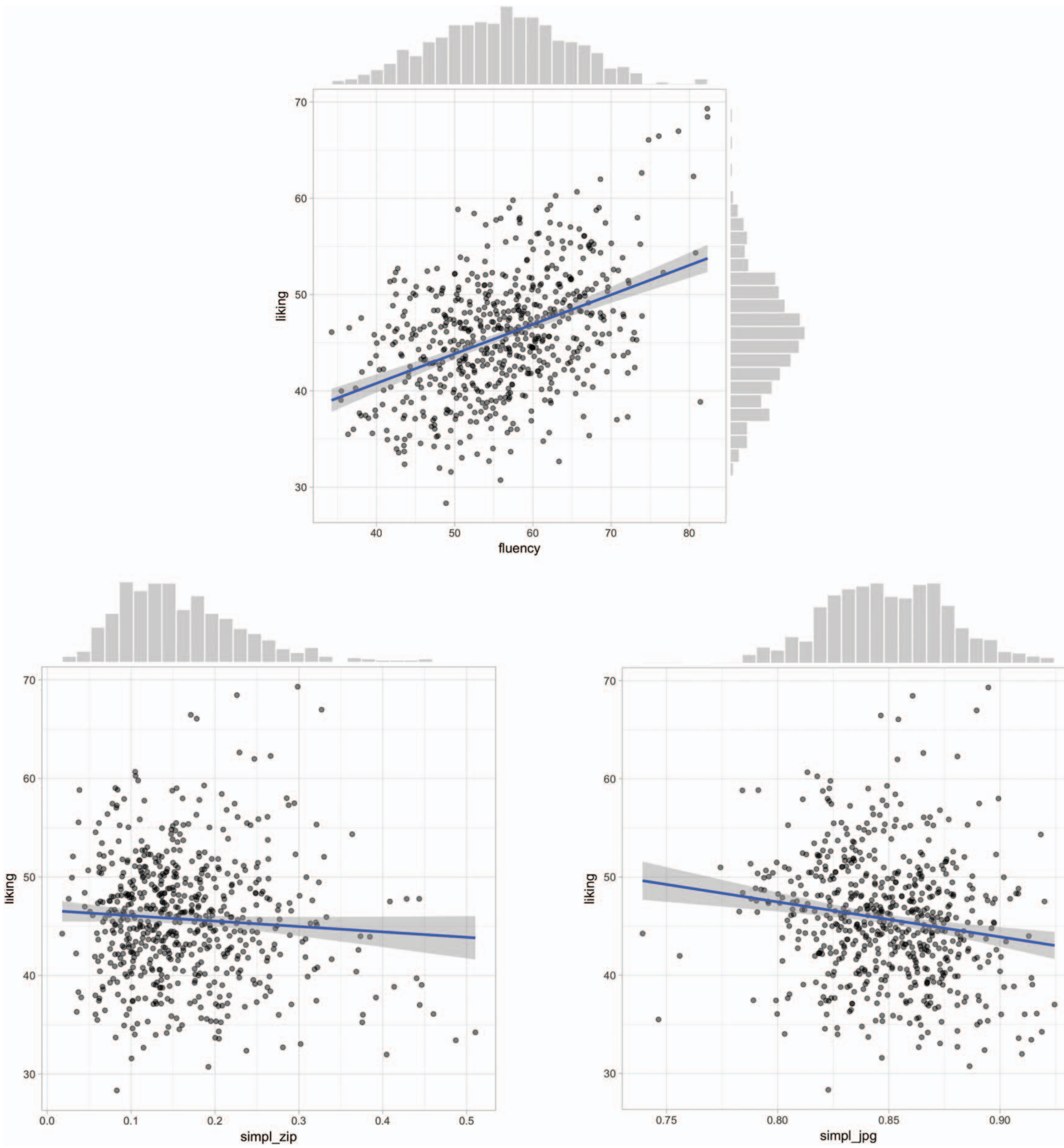
(*Appendices continue*)

Figure D2. Example picture before and after cropping. Pictures are from http://sanbase.com/gallery.html © 2016 San Base. All rights reserved. Used with permission. See the online article for the color version of this figure.

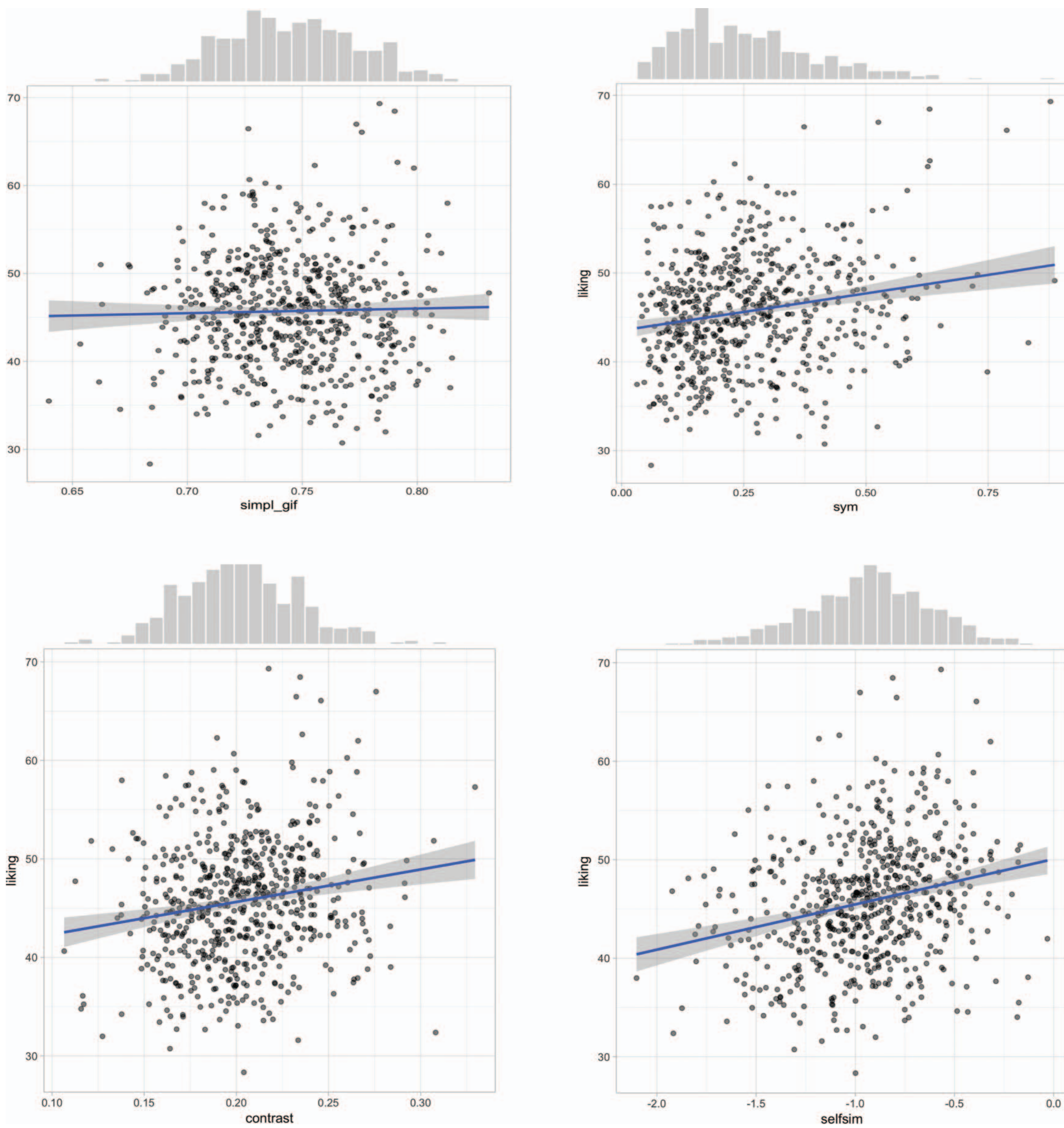
Kappa = 0.588). For our final database, we chose to use only images from the "shapes" and the "foreground and background" categories because these two categories had the highest interrater agreement (Fleiss' Kappa 0.765 and 0.749) and the largest number of images. In particular, we selected all images that were unanimously categorized into these two groups. For this reason, the final resulting number of images in our database is 620. The ratings on aesthetic liking and fluency are based on the cropped images.

(*Appendices continue*)

Appendix E



(*Appendices continue*)



Note. Descriptive Plots of the Variables Used in Study 1. Because Participants Rated Either Liking or Fluency of the Pictures, the Ratings of Liking and Fluency Were Aggregated Per Picture for These Plots. See the online article for the color version of this figure.

(*Appendices continue*)

Appendix F

Linear Mixed Models of Study 1 With Aesthetic Liking as the Dependent Variable, Art Expertise as Control Variable, and Different Image Compression Algorithms for Simplicity

	ZIP simplicity		JPG simplicity		GIF simplicity	
	Estimate [95% CI]	β [95% CI]	Estimate [95% CI]	β [95% CI]	Estimate [95% CI]	β [95% CI]
Fixed effects						
(Intercept)	45.713*** [44.764, 46.663]		45.714*** [44.764, 46.664]		45.713*** [44.763, 46.663]	
Simplicity	−.512* [−1.018, −.0068]	−.018 [−.035, −.00023]	−.280 [−.941, .381]	−.010 [−.033, .013]	.463 [−.095, 1.020]	.016 [−.0033, .035]
Symmetry	.877** [.344, 1.410]	.030 [.012, .049]	.794** [.228, 1.361]	.028 [.0079, .047]	.512 [−.025, 1.048]	.018 [−.00087, .036]
Contrast	.943*** [.451, 1.436]	.033 [.016, .050]	.988*** [.462, 1.514]	.034 [.016, .053]	1.050*** [.575, 1.525]	.036 [.020, .053]
Self-similarity	1.361*** [.873, 1.848]	.047 [.030, .064]	1.265*** [.617, 1.912]	.044 [.021, .067]	1.660*** [1.115, 2.205]	.058 [.039, .077]
Art expertise (AE)	2.424*** [1.568, 3.279]	.084 [.054, .114]	2.424*** [1.568, 3.279]	.084 [.054, .114]	2.424*** [1.568, 3.279]	.084 [.054, .114]
Simplicity*AE	.0021 [−.200, .204]	.000071 [−.0069, .0071]	.124 [−.141, .389]	.0043 [−.0049, .014]	−.072 [−.296, .151]	−.0025 [−.010, .0052]
Symmetry*AE	.041 [−.175, .257]	.0014 [−.0060, .0089]	−.0087 [−.238, .220]	−.00030 [−.0082, .0076]	.067 [−.150, .284]	.0023 [−.0052, .010]
Contrast*AE	−.128 [−.325, .069]	−.0045 [−.011, .0024]	−.085 [−.295, .125]	−.0030 [−.010, .0044]	−.123 [−.313, .066]	−.0043 [−.011, .0023]
Self-similarity*AE	−.038 [−.235, .159]	−.0013 [−.0081, .0055]	.044 [−.217, .305]	.0015 [−.0075, .011]	−.072 [−.292, .148]	−.0025 [−.010, .0051]
Random effects						
N_{id}	1,163		1,163		1,163	
N_{pic}	620		620		620	
ICC_{id}	.259		.258		.259	
ICC_{pic}	.034		.034		.034	
Observations	69,778		69,778		69,778	
R^2/Ω_0^2	.318/.317		.318/.317		.318/.317	

Note. All models include random intercepts per participant (id) and picture (pic). All predictor variables were z-transformed prior to the analysis.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

(*Appendices continue*)

Appendix G

Processing Fluency

Processing fluency theory has been proposed as the underlying psychological mechanism that shapes aesthetic liking judgments (Reber, Schwarz et al., 2004). Thus, to test whether fluency was connected to our four objective aesthetic measures, we ran two additional LMMs with the subjective fluency experience of Study 1 as the dependent variable. As in the main analysis of Study 1, we included random intercepts per participant and picture in the models and z-transformed all predictor variables prior to analysis. The first model again comprised only the four aesthetic measures as predictors (using ZIP/deflate compression to measure simplicity):

$$\begin{aligned} \mathrm{FLUENCY}_{ij} = b_0 + b_1 \times \mathrm{SIMPLICITY}_j + b_2 \times \mathrm{SYMMETRY}_j \\ + b_3 \times \mathrm{CONTRAST}_j \\ + b_4 \times \mathrm{SELF\text{-}SIMILARITY}_j + u_{0i} + u_{0j} + \varepsilon_{ij}. \end{aligned} \tag{7}$$

The second model additionally included participants' art expertise as a control variable (main effect and interactions with the four aesthetic measures):

$$\begin{aligned} \mathrm{FLUENCY}_{ij} = b_0 + b_1 \times \mathrm{SIMPLICITY}_j + b_2 \times \mathrm{SYMMETRY}_j \\ + b_3 \times \mathrm{CONTRAST}_j \\ + b_4 \times \mathrm{SELF\text{-}SIMILARITY}_j \\ + b_5 \times \mathrm{SIMPLICITY}_j \times \mathrm{EXPERTISE}_i \\ + b_6 \times \mathrm{EXPERTISE}_i \\ + b_7 \times \mathrm{SYMMETRY}_j \times \mathrm{EXPERTISE}_i \\ + b_8 \times \mathrm{CONTRAST}_j \times \mathrm{EXPERTISE}_i \\ + b_9 \times \mathrm{SELF\text{-}SIMILARITY}_j \times \mathrm{EXPERTISE}_i \\ + u_{0i} + u_{0j} + \varepsilon_{ij.} \end{aligned}$$

The results of both models are depicted in Appendix H. In the basic model that includes only the four aesthetic characteristics, simplicity ($b = 2.244$, $t = 6.51$, $p < .001$) and symmetry ($b = 2.308$, $t = 6.40$, $p < .001$) are positively related to fluency. Self-similarity ($b = -1.001$, $t = -.03$, $p = .003$), however, is negatively associated with fluency. Contrast cannot be linked to fluency ($b = .079$, $t = 0.23$, $p = .815$). Including art expertise in the model and specifying the interaction terms with the four aesthetic characteristics does not change the direction or the magnitude of the main effects of model 7 (see Appendix H). Art expertise itself contributes positively to fluency ($b = 3.642$, $t = 8.54$, $p < .001$). Participants with higher art expertise judge pictures with higher complexity as more fluent than participants with less art expertise do ($b = -0.374$, $t = -2.26$, $p = .024$).

Overall, the strong positive effects of symmetry and simplicity are consistent with processing fluency theory. The null effect of contrast, however, contradicts the expectations of fluency research. Previous research on contrast has, though, suggested that global contrast might trigger a different process than figure-ground contrast (Tinio et al., 2011), which might be the case in our database. Furthermore, based on previous research on fluency and self-similarity, we expected a positive effect of self-similarity on fluency, which we did not find. More studies on the experiential processes elicited by this visual characteristic are therefore required.

(*Appendices continue*)

Appendix H

Linear Mixed Models of Study 1 With Processing Fluency as the Dependent Variable

	Basic model		With art expertise	
	Estimate [95% CI]	β [95% CI]	Estimate [95% CI]	β [95% CI]
Fixed effects				
(Intercept)	56.104*** [55.093, 57.116]		56.102*** [55.110, 57.093]	
Simplicity	2.244*** [1.568, 2.919]	.082 [.057, .106]	2.235*** [1.559, 2.910]	.082 [.057, .106]
Symmetry	2.308*** [1.601, 3.015]	.084 [.058, .110]	2.304*** [1.598, 3.011]	.084 [.058, .110]
Contrast	.079 [−.579, .736]	.0029 [−.021, .027]	.078 [−.580, .735]	.0028 [−.021, .027]
Self-similarity	−1.001** [−1.647, −.354]	−.037 [−.061, −.013]	−1.005** [−1.651, −.359]	−.037 [−.061, −.013]
Art expertise (AE)			3.642*** [2.806, 4.478]	.133 [.102, .163]
Simplicity*AE			−.374* [−.699, −.050]	−.013 [−.025, −.0018]
Symmetry*AE			.014 [−.324, .351]	.00049 [−.012, .013]
Contrast*AE			.186 [−.127, .499]	.0068 [−.0046, .018]
Self-similarity*AE			−.258+ [−.562, .046]	−.010 [−.021, .0017]
Random effects				
*N*id	1,217		1,217	
*N*pic	620		620	
ICCid	.284		.271	
ICCpic	.062		.063	
Observations	24,339		24,339	
R^2/Ω_0^2	.404/.398		.404/.398	

Note. Two models were estimated: one only with the four objective measures (symmetry, simplicity, contrast, self-similarity), one including self-stated art expertise. Both models include random intercepts per participant (id) and picture (pic). All predictor variables were z-transformed prior to the analysis. $^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

(*Appendices continue*)

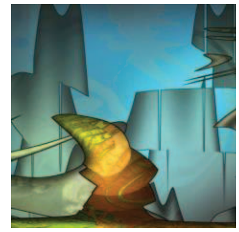
Appendix I

Stimulus Material for Study 2

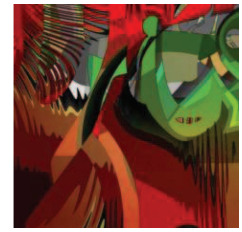
Simplicity

High

Simplicity: 3.588
Symmetry: 0.917
Contrast: 0.319
Self-Sim.: -0.460

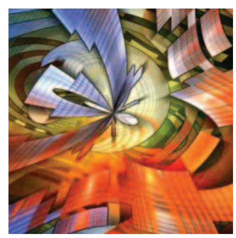


Simplicity: 3.562
Symmetry: 0.445
Contrast: -0.614
Self-Sim.: -0.251



Simplicity: 2.932
Symmetry: -0.169
Contrast: -0.514
Self-Sim.: 0.170

Low



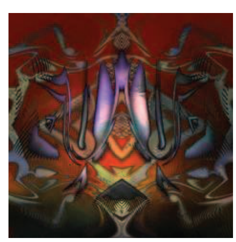
Simplicity: -1.503
Symmetry: 0.078
Contrast: 0.552
Self-Sim.: -0.488

Simplicity: -1.366
Symmetry: -0.493
Contrast: -0.101
Self-Sim.: -0.057

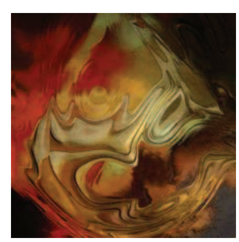
Simplicity: -1.363
Symmetry: -0.495
Contrast: 0.490
Self-Sim.: 0.821

Symmetry

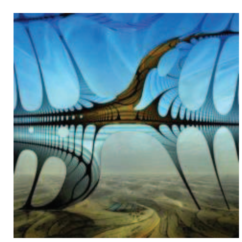
High



Simplicity: 0.786
Symmetry: 3.629
Contrast: -0.802
Self-Sim.: 0.949



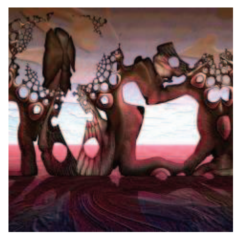
Simplicity: 0.445
Symmetry: 2.662
Contrast: -0.461
Self-Sim.: 0.192



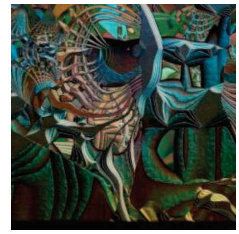
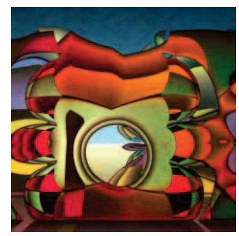
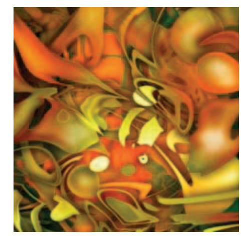
Simplicity: 0.884
Symmetry: 2.463
Contrast: 0.260
Self-Sim.: 0.484

(*Appendices continue*)

Appendix I (*continued*)

	Low	 Simplicity: 0.297 **Symmetry: -1.401** Contrast: -0.121 Self-Sim.: -0.420	 Simplicity: 0.451 **Symmetry: -1.393** Contrast: 0.182 Self-Sim.: 0.782	 Simplicity: -0.968 **Symmetry: -1.361** Contrast: -0.127 Self-Sim.: -0.885
Contrast	High	 Simplicity: 0.590 Symmetry: 0.593 **Contrast: 2.878** Self-Sim.: 0.343	 Simplicity: -0.703 Symmetry: -0.297 **Contrast: 2.799** Self-Sim.: -0.566	 Simplicity: 0.233 Symmetry: 0.944 **Contrast: 2.739** Self-Sim.: 0.223
	Low	 Simplicity: -0.170 Symmetry: -0.440 **Contrast: -2.144** Self-Sim.: 0.566	 Simplicity: -0.747 Symmetry: -0.566 **Contrast: -2.004** Self-Sim.: -0.138	 Simplicity: 0.405 Symmetry: 0.119 **Contrast: -1.928** Self-Sim.: 0.305

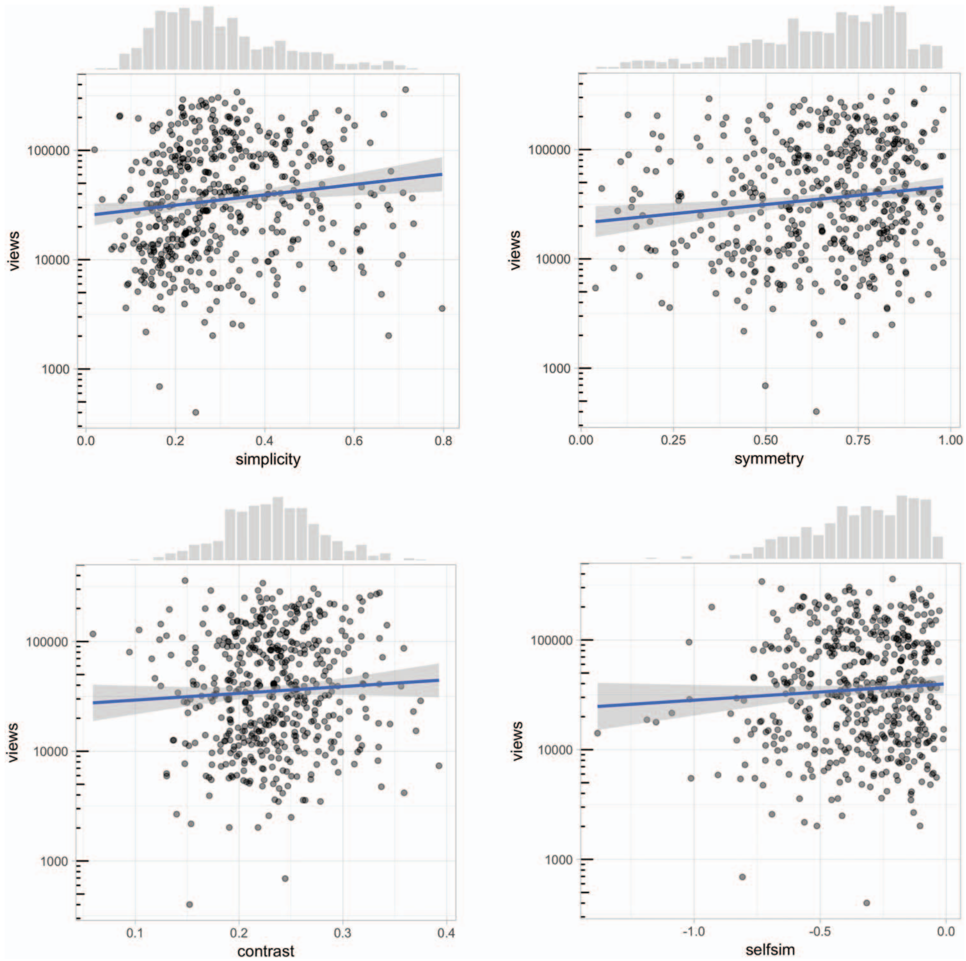
(*Appendices continue*)

Self-similarity (Self-sim.)	High	 Simplicity: -0.292 Symmetry: -0.084 Contrast: -0.188 **Self-Sim.: 2.453**	 Simplicity: -0.361 Symmetry: 0.246 Contrast: 0.962 **Self-Sim.: 2.318**	 Simplicity: -0.447 Symmetry: -0.821 Contrast: 0.252 **Self-Sim.: 2.044**
	Low	 Simplicity: -0.808 Symmetry: -0.348 Contrast: 0.575 **Self-Sim.: -2.688**	 Simplicity: 0.548 Symmetry: 0.115 Contrast: 0.985 **Self-Sim.: -2.440**	 Simplicity: -0.984 Symmetry: -0.892 Contrast: -0.147 **Self-Sim.: -2.342**

Note. The table includes the z-scores of the stimuli on each of the four dimensions. The z-scores are based on a previous version of the measures that used grayscale instead of color images; moreover, they all score between minus one and plus one on visual typicality (cf. Footnote 5 in the article). Pictures from http://sanbase.com/gallery.html © 2016 San Base. All rights reserved. Used with permission. See the online article for the color version of this figure.

(*Appendices continue*)

Appendix J



Note. Descriptive Plots of The Variables Used in Study 3 (Scatterplots With The Log-Transformed Number of Flickr Views). See the online article for the color version of this figure.

Received October 21, 2016
Revision received February 2, 2018
Accepted April 19, 2018 ■