Acta Psychologica 202 (2020) 102936

Contents lists available at ScienceDirect

Acta Psychologica

journal homepage: www.elsevier.com/locate/actpsy

Abstract art paintings, global image properties, and verbal descriptions: An empirical and computational investigation

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ARTICLE INFO

Keywords:
Abstract art
Network
Description
Image properties

ABSTRACT

While global image properties (GIPs) relate to preference ratings in many categories of visual stimuli, this relationship is typically not seen for abstract art paintings. Using computational network science and empirical methods, we further investigated GIPs and subjective preferences. First, we replicated the earlier observation that GIPs do not relate to preferences for abstract art. Next, we estimated the network structure of abstract art paintings using two approaches: the first was based on verbal descriptions and the second on GIPs. We examined the extent to which network measures computed from these two networks (1) related to preference for abstract art paintings and (2) determined affiliation of images to specific art styles. Only semantic-based network predicted the subjective preference ratings and art style. Finally, preference and GIPs differed for sub-groups of abstract art paintings. Our results demonstrate the importance of verbal descriptors in evaluating abstract art, and that it is not useful in empirical aesthetics to treat abstract art paintings as a single category.

1. Introduction

Until the early 20th century, art paintings typically representated the external world (people, landscapes, animals and still life). Perhaps because of the advent of photography, some artists began to create paintings without reference to real-world objects. While rejected initially, these abstract art paintings are now common displayed in art galleries. Nevertheless, people with little exposure to the arts prefer representational paintings over abstract paintings (Cattaneo et al., 2015). Furthermore, people are more consistent in their preference ratings for representational art than abstract art paintings (Brinkmann, Commare, Leder, & Rosenberg, 2014; Vessel & Rubin, 2010). The question arises: Why do preferences for abstract art paintings vary across people? To tackle this question, we tested two hypotheses: (1) subjective verbal descriptions of visual stimuli influence people's preferences; (2) objective psychophysical properties of visual images influence people's preference. We applied correlational and computational methods to investigate how people vary in their preference for abstract art paintings.

1.1. Verbal descriptions and evaluations of art paintings

People can verbalize their impression of visual stimuli. The terms most often associated with aesthetics are 'beauty' and 'ugly' (Jacobsen, Buchta, Köhler, & Schröger, 2004). For visual art, 'beautiful', 'ugly', 'colorful' and 'abstract' are used most frequently (Augustin, Wagemans, & Carbon, 2012). One can further differentiate between verbal descriptions (i.e., terms that characterize the stimulus) and verbal evaluations (i.e., terms that refer to subjective impressions evoked by the stimulus). Marković and Radonjić (2008) asked participants to label eight images, mostly representative art paintings from different art styles, and found correlations between verbal descriptions (e.g., form, color) and evaluations (e.g., pleasantness, interestingness). Similarly, in a study of abstract art paintings, Lyssenko, Redies, and Hayn-Leichsenring (2016) found that verbal descriptive ('structure') correlated with evaluative ('interestingness') ratings.

1.2. Global image properties and evaluation of images

Formalist approaches focus on objective psychophysical image properties. One family of such objective properties is Global Image Properties (GIP), i.e. objective features that refer to the entire image

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https://doi.org/10.1016/j.actpsy.2019.102936
Received 16 April 2019; Received in revised form 27 August 2019; Accepted 16 September 2019
0001-6918/

rather than its components. GIPs apply higher-order statistics to the image. Examples of GIP measures are fractality, self-similarity, overall complexity, overall anisotropy and overall color values. GIPs can be used to categorize images. For instance, photographs of natural scenes are typically more self-similar than visual artworks, cartoons, photographs of objects and photographs of faces (Amirshahi, Koch, Denzler, & Redies, 2012). Also, distinct patterns of GIPs are found for specific styles of representative art (Hayn-Leichsenring, Lehmann, & Redies, 2017).

If psychophysical properties of visual images can influence people's preference, then GIPs would be a plausible candidate measure to correlate with subjective evaluations within image categories. The most commonly tested subjective evaluation is preference. People prefer face photographs with lower self-similarity and lower complexity (Menzel, Hayn-Leichsenring, Langner, Wiese, & Redies, 2015). They prefer less self-similar landscape paintings, still life, portrait paintings and paintings of urban scenes, and less complex portrait paintings (Hayn-Leichsenring et al., 2017).

If psychophysical properties influence people's preference, GIPs should also correlate with preference ratings in abstract art paintings. We might expect these correlations to be especially robust since abstract art paintings lack figurative content. Therefore, objective psychophysical properties are the main source on which preferences might be based within these stimuli. While GIPs correlate with verbal descritions in abstract art paintings (e.g., self-similarity correlates with subjective 'complexity' and 'structured' ratings), they do not appear to correlate with preference (Lyssenko et al., 2016; Mallon, Redies, & Hayn-Leichsenring, 2014).

One potential explanation for the lack of relation between GIPs and preference for abstract art is that people's taste for these paintings varies. If people are segregated based on their preferences for certain abstract art paintings, GIPs correlate with preference ratings in abstract art paintings (Mallon et al., 2014). Another possibility is that abstract art paintings are not a single category. Perhaps GIPs relate to people's preferences for abstract art paintings when considering only a sub-set of abstract art paintings. In a study that only focused on abstract art paintings by a single artist (Christoph Redies), self-similarity correlated negatively with ratings of 'interestingness' (evaluative), and complexity correlated negatively with ratings of 'harmony' (evaluative) (Redies, Brachmann, & Hayn-Leichsenring, 2015).

The evidence for the relationship of GIPs to evaluations of abstract art paintings is mixed. Here, we revisit this issue using network science, to examine the relation between verbal descriptions, GIPs and preference ratings for abstract art paintings.

1.3. Network science

Computational tools from network science have been applied recently to study cognitive and psychological constructs (Christensen, Kenett, Aste, Silvia, & Kwapil, 2018; Epskamp, Maris, Waldorp, & Borsboom, 2015; Siew, Wulff, Beckage, & Kenett, 2019). This approach is based on mathematical graph theory, providing quantitative methods to investigate complex systems as networks (Barabási, 2016). A network is comprised of nodes, that represent the basic unit of the system (e.g., an abstract art image) and links, or edges, that signify the relations between the nodes (e.g. GIP-based or verbal descriptor-based similarity).

Recent network science methods have investigated cognitive phenomena such as the structure of language and memory (Baronchelli, Ferrer-i-Cancho, Pastor-Satorras, Chater, & Christiansen, 2013; Borge-Holthoefer & Arenas, 2010; Siew, Wulff, Beckage, & Kenett, 2019). Cognitive networks, for example, have identified mechanisms of language development (Hills, Maouene, Maouene, Sheya, & Smith, 2009; Steyvers & Tenenbaum, 2005), shown that specific network parameters influence memory retrieval (Vitevitch, Chan, & Roodenrys, 2012; Vitevitch, Chan, & Goldstein, 2014; Vitevitch, Goldstein, & Johnson, 2016), related network parameters to individual differences in creativity (Kenett & Faust, 2019), and provided new insight into the semantic structure of second languages in bilinguals (Borodkin, Kenett, Faust, & Mashal, 2016).

Here, we used verbal descriptors of different abstract art paintings to estimate a semantic-based network of the relations between such abstract art paintings (Siew et al., 2019). Similarly, we used GIPs to estimate a GIP-based network of the relation between the same abstract art paintings. We examined how properties of both networks relate to preference ratings of abstract art paintings. This analysis allowed us to quantitatively examine how verbal descriptions or GIPs relate to participant's preferences for these abstract art paintings. This approach further allowed us to examine how the abstract art paintings in both networks cluster into sub-groups based on a data-driven approach and how these sub-groups relate to art styles. Thus, this computational network approach allows us to directly examine our two hypotheses regarding the relationship between GIPs, verbal descriptors and preference for abstract art paintings.

1.4. Aim of the studies

In Study 1, we aimed to replicate previous findings that show that figurative visual stimuli correlate with GIPs, but abstract art paintings do not. We correlated GIPs with preference ratings for nine different stimuli sets (houses, faces, etc.), including abstract art paintings. In Study 2, we re-analyzed verbal descriptions and GIPs of abstract art paintings – data collected by Lyssenko et al. (2016) – using a computational network analysis. This analysis allowed us to examine how properties of the network based on verbal desciptions and the network based on GIPs relate to preferences for abstract art paintings. Such an analysis further allowed us to computationaly examine how abstract art paintings cluster into sub-groups (Siew et al., 2019), and whether semantic-based and GIP-based clusters relate to culturaly and historically defined art styles. In Study 3, motivated by sub-groups identified in Study 2, we conducted a more constrained examination of the relationship between GIPs and preferences in abstract art paintings produced by specific artists.

2. Study 1

2.1. Introduction

In Study 1, we aimed to replicate the results of previous studies (Hayn-Leichsenring et al., 2017; Lyssenko et al., 2016; Mullin, Hayn-Leichsenring, Redies, & Wagemans, 2017) on the relation between GIPs and preference ratings across various image categories. We analyzed nine different categories of images (face photographs, art portraits, cars, landscape photographs, landscape paintings, landscape drawings, house facades, magazine cover, photos of art installations and abstract art paintings). We predicted that for abstract art paintings, GIPs would correlate poorly with preference ratings, while correlations would be found for other image categories.

2.2. Methods

2.2.1. Participants

Sixty-six participants participated in the study. Six participants were excluded from the original group because of data collection issues leaving sixty participants in the final dataset (18–31 years; $M = 23.1$ years [$SD = 3.0$]; 14 male). The study was approved by the ethics committee of the Universitätsklinikum Jena. Participants stated their consent by signing a consent form.

2.2.2. Stimuli

We used nine types of images (cars, house facades, magazine cover, face photographs, art portraits, landscape photographs, landscape drawings, landscape paintings, photos of art installations and color abstract art paintings). Each category contained 100 images, except for the car category, which had 96 images. Cars, house facades and magazin covers were taken from Braun, Amirshahi, Denzler and Redies (2013), face photographs were randomly selected from the FACES database (Ebner, Riediger, & Lindenberger, 2010), art portraits and landscape paintings were a subset from the JenAesthetics database (Amirshahi, Denzler, & Redies, 2013), landscape photographs and landscape drawings were taken randomly from a database established by Redies, Hasenstein, and Denzler (2007), photos of art installations were collected online for a previous study (Schulz & Hayn-Leichsenring, 2017) and images of abstract art were taken randomly from a database established by Mallon et al. (2014).

2.2.3. Global image properties

For each of the images, we computed the following Global Image Properties (GIPs) with MATLAB (Amirshahi et al., 2012): Pyramidal Histogram of Gradients Self-Similarity, Histogram of Gradients Complexity, Histogram of Gradients Anisotropy, color hue, color saturation, color value, and aspect ratio. In the following paragraphs, these measures will be explained briefly.

2.2.3.1. Pyramidal histogram of oriented gradients (PHOG) self-similarity. A Histogram of Oriented Gradients (HOG) is created for every image. In these histograms, the mean strength of the luminance gradients is binned in 16 equally sized orientations (Dalal & Triggs, 2005). This GIP measure is used to compute the self-similarity of an image, by comparing the HOG from the entire image with HOGs from equal subparts of the image (Bosch, Zisserman, & Munoz, 2007). The image is divided into 4 (level 1), 16 (level 2) and 64 (level 3) rectangles of similar size. Then, the HOG features of the entire image (level 0) are compared with the HOG features of the sub-images (levels 1–3) using the Histogram Intersection Kernel (Amirshahi et al., 2012). Self-similarity in this sense implies that an object as a whole is similar to its parts (Braun, Amirshahi, Denzler, & Redies, 2013). Higher values of this measure stand for greater self-similarity. An example of an abstract art painting with high self-similarity is Gerhard Richter's "4096 Farben" – a painting consisting of 4096 similar-sized squares of different colors. In contrast, e.g., Morris Loius' "Gamma Tau" – a largely white canvas with colorful angular lines on the far sides – has low self-similarity.

2.2.3.2. Histogram of gradients (HOG) complexity. The complexitiy of an image can be measured in different ways. Here, we applied a measure based on gradient strength. Image gradients represent changes of lightness). Thus, the mean norm of the gradients across all orientations in the image was used as an estimate for image complexity (HOG complexity; Braun et al., 2013). Higher values in HOG complexity relate to higher overall strength of gradient and, therefore, higher objective complexity (e.g., the image appears to be more detailed). An example of an abstract art painting with high complexity is Jean Dubuffet's "Site Inhabited by Objects" – a painting with various flat interlocking shapes. In contrast, e.g., Ad Reinhardt's "Abstract painting No. 5″ – a black square on white ground – possesses low complexity.

2.2.3.3. HOG anisotropy. Anisotropy is a measure of the heterogeneity of luminance gradients in an image, which we measure as the distribution of orientation of gradients within an image. In these histograms, we binned the mean strength of orientation gradients in 16 equally-sized bins. Then, we compared the mean strength for every gradient orientation (Braun et al., 2013). High values in anisotropy imply that one or few orientations of gradients are more prominent than others in the HOGs. In contrast, low values indicate a rather uniformly distributed luminance gradient across all orientations (Redies, Amirshahi, Koch, & Denzler, 2012). An example for an abstract art painting with high anisotropy is Frank Stella's "Hyena Stomp" – a very colorful paintings consisting of straight stripes. In contrast, e.g., Yves Klein's "Cosmogonie de l'orage" – a blue pattern with sprinkles of various sizes and orientations – possesses low anisotropy.

2.2.3.4. Color measures (hue, saturation, value). For global color measures we used hue, saturation and value (HSV) (Smith, 1978) to characterize the images. Color hue refers to the pure spectrum colors (the degree to which a stimulus can be described as similar or different from red/green/blue/yellow); color saturation describes the intensity/purity of the color; color value is a measure for the relative lightness/darkness of a color.

2.2.3.5. Aspect ratio. The aspect ratio of an image is calculated by dividing image height by image width. While there seems to not be an overall preference for a certain aspect ratio in paintings (McManus, 1980; Russell, 2000), certain subject matters are preferred in certain aspect ratios (e.g., portrait paintings in upright format, landscape paintings in landscape format; Hayn-Leichsenring et al., 2017).

2.2.4. Statistical analysis

We calculated Pearson's *r* coefficients for the correlation of preference ratings with seven GIPs for each of the image categories, corrected for multiple comparisons.

2.2.5. Procedure

Because of the length of the experiment, we divided the sixty participants into three groups (twenty participants per group). Each group rated three or four categories of stimuli in randomized order. The first group rated cars, house facades, art portraits (on their attractiveness) and landscape drawings. The second group rated magazine covers, landscape photographs, photographs of art installations and abstract art paintings. The third group of participants rated face photographs, art portraits (on their beauty) and landscape paintings. Aesthetic responses occur rapidly, consistently and automatically (Mullin et al., 2017). Therefore, we used a short presentation time of 50 ms (we also performed the same experiment with a presentation time of 3000 ms, leading to similar results). The order of the images was randomized within category. After image presentation, a random-phase Fourier mask (1000 ms) was shown to avoid afterimages. Since art portraits can elicit two types of hedonic responses (namely the attractiveness of the depicted person and the beauty of the painting itself, see Schulz & Hayn-Leichsenring, 2017), the art portraits assesment was run in two trials by different groups of participants. The first group rated images for attractiveness of the person being depicted, the second group rated images for beauty of the image. While this distinction between the attractiveness of the object being depicted and the beauty of the image itself applies to any figurative image, all other kinds of stimuli were rated only on overall preference. For every rating, we used a continuous scale (100 points) from "not beautiful" (German "nicht schön") to "beautiful" (German: "schön") or "not attractive (German: "nicht attraktiv") to "attractive" (German: "attraktiv).

2.3. Results

We computed correlations for each of set of stimuli between the seven different GIPs and mean values across participants. Based on previous studies (Braun et al., 2013; Menzel et al., 2015; Redies et al., 2007), magazine covers, face photographs, landscape photographs and landscape drawings were presented in grayscale. Therefore, color measured (hue, saturation and value) were not calculated for these stimuli. There are no aspect ratio correlations for face photographs, cars, landscape photographs and magazine covers, because the images were square.

We found different correlations of preference ratings with GIPs for the respective stimuli sets (see Fig. 1). For instance, ratings of

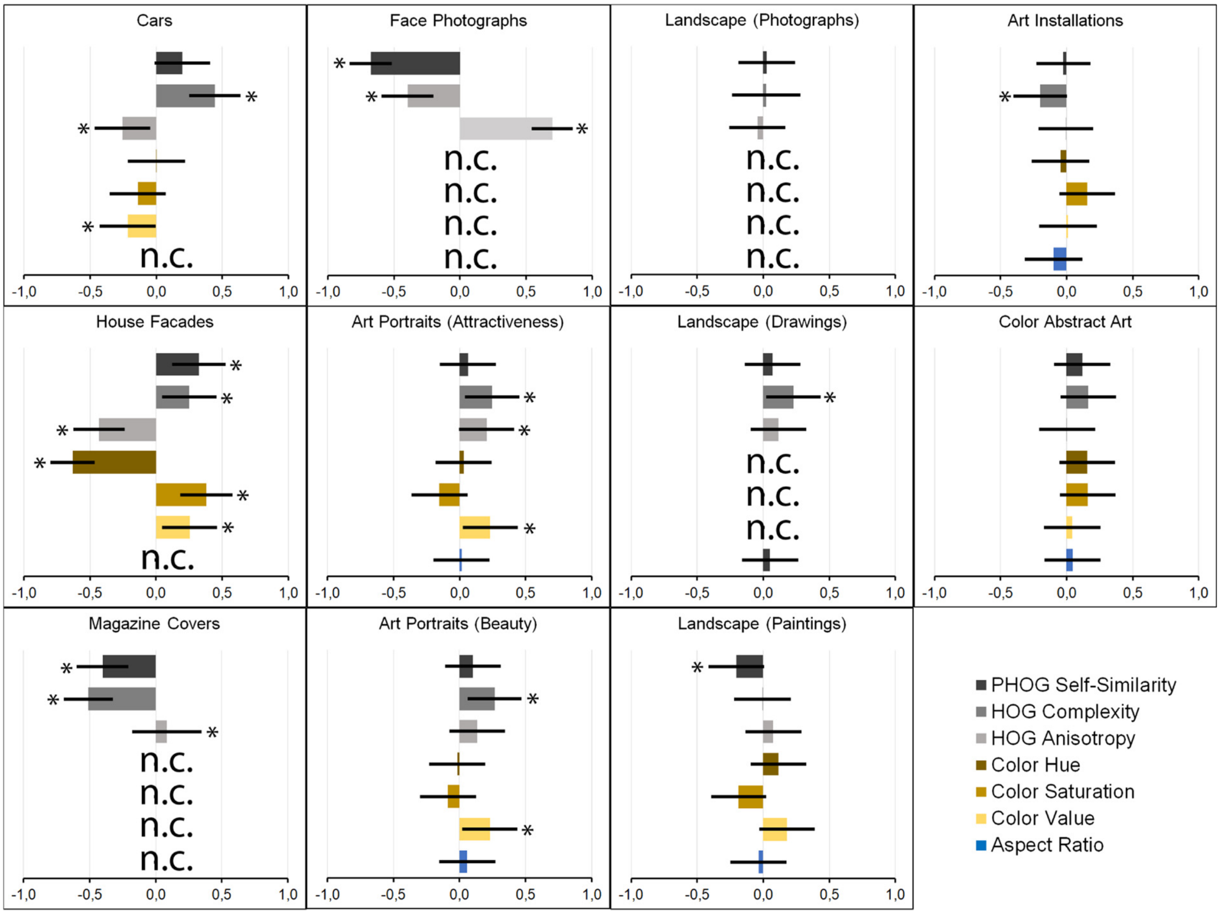

Fig. 1. Pearson's *r* coefficients for the correlation of preference ratings (presentation time = 50 ms) with GIPs across the different datasets. * = $p < .05$, Bonferroni-corrected. n.c.: GIP not calculated for this category. Bars indicate confidence intervals.

landscapes correlated negatively with self-similarity, $r = -0.38$, $p < .001$. This result is in line with previous studies (Mullin et al., 2017). In contrast, more self-similar house facades were preferred, $r = .21$, $p < .001$. There were no correlations of preference ratings with GIPs for abstract art paintings (see Supplemental Table 1 for detailed results on both presentation times and see Supplemental Table 2 for significant differences of Pearson's *r* values between abstract art and the other stimulus sets).

2.4. Discussion

Study 1 showed that preference ratings correlated with GIPs for figurative images (face photographs, portrait paintings, cars, landscape paintings, landscape drawings, house facades, magazine covers and art installations), but not for abstract art paintings. Although this finding is in line with previous studies (Hayn-Leichsenring et al., 2017; Lyssenko et al., 2016; Mullin et al., 2017), it remains surprising. As mentioned before, one would predict that the lack of figurative content in abstract art paintings might lead to a higher influence of form (as represented by GIPs) on preference ratings.

3. Study 2

3.1. Introduction

In Study 2 we further explored the relation between GIPs, verbal descriptors and preferences for abstract art paintings. We applied a computational network science approach to estimate semantic-based and GIP-based networks of abstract art paintings and examined how properties of these networks relate to preference ratings of these paintings. Such analysis allowed us to compare the role of verbal descriptors and GIPs in how people prefer abstract art paintings. Furthermore, such a quantitative approach allowed us to examine if these abstract art paintings organize into clusters which relate meaningfully to art styles.

To this aim, we re-analyzed previously collected behavioral data and GIPs of abstract art paintings. Lyssenko et al. (2016) collected behavioral data (verbal descriptions AND preference ratings) and GIPs of abstract art paintings. We used our semantic-based and GIP-based network analysis of the data collected by Lyssenko et al. (2016) to examine whether (subjective) verbal descriptors and (objective) GIPs relate differently to subjective preferences.

3.2. Method

3.2.1. Participants

We reanalyzed data collected by Lyssenko et al. (2016) who performed two separate studies. Their first study ('Description') enrolled 19 participants (19–37 years; Mean = 22.8 years; 13 female). Their second study ('Rating') enrolled 42 participants (19–31 years, Mean = 23.5 years; 28 female). The original study was approved by the ethics committee of the Universitätsklinikum Jena. The participants stated their consent by signing a consent form.

3.2.2. Stimuli

The stimuli included 79 images of abstract art paintings taken from a dataset of 150 images of abstract art paintings compiled by Mallon et al. (2014). The paintings were categorized by art style (Action

Painting, Color Field Painting, Constructivism, Suprematism, and Other). We assigned paintings and/or artists to specific art periods based on various publications on abstract art (Böthig & Hayn-Leichsenring, 2017). The assignment to art styles was used to determine if network clustering analysis followed these cultural and historical stylistic categories.

3.2.3. Global image properties

We calculated the same GIPs as in Study 1 (self-similarity, complexity, anisotropy, color hue, color saturation, color value and aspect ratio). These seven GIPs were used in the original study by Lyssenko et al. (2016).

3.2.4. Verbal descriptors and preference

3.2.4.1. Description. Participants sat in front of a computer screen and saw each painting for 30 s. They were instructed to verbally describe the 79 paintings by producing (German) adjectives that characterized the displayed image of a particular abstract art painting. These adjectives were written down by the experimenter.

3.2.4.2. Rating. Participants saw each image for 3 s and rated them on five different scales (complexity, structure, emotion, interest, and preference). However, for the present study, we only used the preference ratings ('do not like' (gefällt mir nicht) to 'like' (gefällt mir)) as the dependent variable in our analyses.

For a detailed description of the procedure, see Lyssenko et al. (2016).

3.2.5. Network estimation

The semantic-based and GIP-based networks were estimated using a network approach developed to analyze free association data (Kenett, Anaki, & Faust, 2014). According to this approach, each node represents an image and edges between nodes represents the association between two images. These associations represent the similarity profiles across any pair of images. For the semantic-based network, such a similarity profile represents the overlap of adjectives generated by the sample to each of the images. For the GIP-based network, such a similarity profile represents the overlap of the seven GIP measures computed for each of the image.

The networks were estimated in the following way: First, both data matrices (semantic and GIP) were structured with each column as an image, and each row as a unique variable (adjective descriptor or GIP). Thus, each cell denotes a value for a specific unique variable i to an image j. For the semantic-based matrix, each cell denotes how many participants generated unique adjective i to image j. For the GIP-based matrix, each cell denotes the value of the unique GIP i to image j. Second, the correlation between any pair of images for both types of networks was calculated using Pearson's correlation. This resulted in a 79×79 matrix where each cell denotes the semantic/GIP correlation between node i and node j.

Finally, many edges have small values or weak associations, representing noise in the network. To minimize noise and possible spurious associations, we applied a planar maximally filtered graph filter to remove spurious correlations (Christensen et al., 2018; Kenett et al., 2014; Tumminello, Aste, Di Matteo, & Mantegna, 2005). This approach retains the same number of edges between the groups and avoids the confound of different network structures arising from different number of edges (Christensen et al., 2018; van Wijk, Stam, & Daffertshofer, 2010). Thus, the networks constructed by this approach can be compared directly because they have the same number of nodes and edges. To examine the structure of the networks, the edges are binarized so that all edges are converted to a uniform weight (i.e., 1). Although the networks could be analyzed using weighted edges (weights equivalent to the similarity strength), this potentially adds noise to the interpretation of the structure of the network. Thus, the networks are analyzed as unweighted (all weights are treated as equal) and undirected (bidirectional relations between nodes) networks.

3.2.6. Network analyses

Analyses were performed with the Brain Connectivity Toolbox for MATLAB (Rubinov & Sporns, 2010). The clustering coefficient (CC; measuring network connectivity), the average shortest path length (ASPL; measuring global distances), and modularity (Q; measuring communtity structure) were calculated (Fortunato, 2010; Newman, 2006; Siew et al., 2019).

The clustering coefficient of a node refers to the extent that two neighbors of a node will themselves be neighbors (i.e., a neighbor is a node i that is connected through an edge to node j). Thus, a higher CC relates to higher overall connectivity in the network. In semantic networks, such connectivity denotes the similarity between concepts, and can be similarly applied in GIP-based networks. The ASPL refers to the average shortest number of steps (i.e., edges) needed to traverse between any pair of nodes, e.g., the higher the ASPL, the more spread out a network is. Previous research at the semantic level have shown that ASPL between concepts in semantic networks corresponds to participants judgments whether two concepts are related to each other (Kenett, Levi, Anaki, & Faust, 2017). The network's CC and ASPL were evaluated qualitatively against the equivalent parameters in a random network with the same number of nodes and edges (CC_{rand} and $ASPL_{rand,}$ respectively). The modularity (Q) measure identifies how a network breaks apart (or partitions) into smaller sub-networks or *communities* (Fortunato, 2010; Newman, 2006). The modularity statistic (Q) measures the extent to which the network has dense connections between nodes within a community and sparse (or few) connections between nodes in different communities. Thus, the higher Q is, the more the network breaks apart to subcommunities. Such subcommunities can be subcategories in a semantic network, or clusters of artstyles in an image network.

3.2.7. Relating network measures to abstract art paintings preference

To examine how well the semantic- and GIP- based networks relate to preferences, we computed local network measures from both networks and related them to preference ratings of the images. Local network measures are computed for each of the nodes in both networks and included the local clustering coefficient, the local average shortest path length, degree, betweenness centrality, eigenvector centrality, and core/periphery. The *local clustering coefficient (C_i),* which is the average of each node's clustering coefficient vector (Christensen et al., 2018). The *local average shortest path length ($ASPL_i$)* is the average distance for each node to all other nodes (Christensen et al., 2018). *Betweenness centrality* (BC) measures the extent a node lies on the paths between other nodes (Freeman, 1977). Therefore, nodes with high betweenness values make up the most central elements or "backbone" of the network (Borgatti, 2005). *Degree* (k), the number of connections a node has, is a basic measure of a node's importance, and its distribution reveals important information about the type of network. *Eigenvector centrality* (EC) is the weighted sum of direct and indirect connections of a node and is an index of the quality of connections for each node (Bonacich & Lloyd, 2001). For example, the EC distinguishes a node of low degree that is connected to many high degree nodes and a high degree node that is connected to only low degree nodes (Bonacich, 2007). Thus, higher EC values are given to nodes that have connections to other central nodes (van Borkulo et al., 2015). *Core/periphery* measures whether node i is in the core or periphery of the network (Borgatti & Everett, 2000).

3.2.8. Community analysis

Finally, we conducted community detection analyses to examine how well the images (nodes) in the network cluster into well-defined artistic style. To do so, we use a data driven approach to determine community assignment of each node in both networks (Betzel et al., 2017). We applied a modularity maximization approach that aims to partition a network into communities. This approach uses the Louvain modularity method, a greedy stochastic method (Lancichinetti & Fortunato, 2009). Given the stochasticity of this method, the application of the Louvain modularity method is reiterated 1,000 times (Bassett et al., 2011). To resolve the variability across the 1,000 iterations of the community assignment partitions, a consensus analysis is conducted to identify the community assignment partition that summarizes the commonailities across the entire distribution of partitions (Betzel et al., 2017; Lancichinetti & Fortunato, 2012). The results of this process are data-driven consenses-based identified communities for each of the networks and community assignment of each of the images (nodes) in the network to a specific community.

Then, we calculated the mean values for GIPs and the preference ratings on the various scales of the images from single communities for both the semantic-based and the GIP-based networks. We used the standard deviation of the values as an indicator for how much they differ. Then, we calculated Pearson's *r* coefficients for correlations between GIPs and mean preference ratings for the single communities of the semantic-based cluster and compared them with correlation coefficients over all images.

3.3. Results

Participants generated a total of 4447 adjectives (1447 unique adjectives) to describe the images. There were on average 56.29 adjectives per image (or 2.96 adjectives per image per participant). The verbal descriptions of the images and the GIPs of the images were used to estimate semantic-based and GIP-based networks, as described above (Table 1). To visualize the networks (Fig. 2), we applied the force-directed layout of the Cytoscape software (Shannon et al., 2003). In these 2D visualizations, nodes are represented by the respective images and edges between them are represented by lines. Since these networks are undirected and weighted, the edges convey symmetrical (i.e., bidirectional) similarities between two nodes.

Next, we computed the local level network measures for all nodes in both networks, as described above. We then conducted a Pearson's correlation analysis to examine the relation of each of the local level network measures in both networks and the preference ratings of all images. This analysis was conducted for each network separately. This analysis revealed only a marginal positive correlation between the local ASPL measures in the semantic-based network and the preference ratings of the images, $r = .22, p = .057$, 95 % confidence interval -0.006 to .437 (Fig. 3): The further a node was from all other nodes in the network, the higher the preference rating it received. Thus, the more distinctive an image is from other images in the semantic-based network, the more it was preferred.

Finally, we computed the consensus community assignment partition for both networks, as described above. This analysis identified six communities in both networks, with different node assignment into these communities. We then calculated the mean values of GIPs (Supplemental Table 4) and preference ratings (Supplemental Table 5) for each community of both networks. We found that the semantic-based network was better in separating preference ratings (i.e., ratings that were acquired from different participants than the verbal descriptions).

Table 1
Network measures for the semantic-based and GIP-based networks.

	Semantic	GIPs
CC	.69	.68
ASPL	4.11	5.16
Q	.64	.65
CC_{rand}	.05	.09
$ASPL_{rand}$	2.59	2.61

Note - GIPs – Global Image Properties; CC – clustering coefficient; ASPL – average shortest path length; Q – modularity measure; CCrand – Clustering coefficient of random graph; ASPLrand – average shortest path length of random graph.

The designation of art styles permits the grouping of abstract art painting into related sub-groups (Fernie, 1995). We categorized the images by art styles and investigated whether images from the same art style are assigned to the same community (Table 2, see also Böthig & Hayn-Leichsenring, 2017). The semantic-based network was better at differentiating art styles (represented by higher standard deviations of the distribution to communities; mean value for the $SD_{Semantic} = 2.63$, mean $SD_{GIP} = 1.47$). This worked especially well for Action Paintings. Thirteen of the twenty Action Paintings were assigned to one particular community (C2). The differentiation worked moderately for Suprematism and Constructivism in GIP-based network.

We investigated whether the images in the different communities exhibit different correlation patterns between GIPs and preference ratings (Fig. 4). While this analysis revealed several weak to medium correlations (Pearson's *r* up to .8), none of these correlations survived corrections for multiple comparisons (Fig. 4). The low number of images per community (5–25) might have prevented identifying true correlations, even though the tendencies hinted at possible associations.

3.4. Discussion

We applied computational network science methods to examine the roles of verbal descriptors and GIPs in people's preferences for abstract art paintings by estimating semantic-based and GIP-based networks and examining how properties of these networks related to preferences. Verbal descriptions correlated with GIPs (Lyssenko et al., 2016). We only found marginal correlations between the local distance measure (measuring how many steps are needed to be taken from a specific node to all other nodes) in the semantic-based network and preference ratings of the abstract art images: Nodes (images) that were farther away – more distinct – from all other images, in how they were described, were most preferred. Thus, properties of the semantic-based network – estimated from verbal descriptors of the abstract art paintings – are more closely related to people's preferences than those of the GIP-based network, despite the fact that one would expect preference for abstract art paintings to rely in formal properties of the image. Furthermore, we found several trends between GIPs and preference ratings in single communities. These tendencies do not reach significance

We also found that the semantic-based network classifies images according to their art style better than the GIP-based network. Our participants described abstract art paintings from apecific art styles with similar terms, but paintings from specific art styles did not have similar GIPs.

The findings of Study 2 – a semantic-based network relates to preference ratings and is more useful to classify abstract art paintings according to their art style – highlight the role of semantic descriptions on people's preferences for abstract art paintings. This finding is surprising since abstract art paintings lack figural content and are, therefore, relatively poor in semantic content. Furthermore, the findings of Study 2 demonstrate that when abstract art paintings are divided into subgroups (based on semantic descriptions), relations between GIPs and preference ratings emerge (see Fig. 3). However, none of these relations reach significance. Therefore, we pursued this finding in Study 3.

4. Study 3

4.1. Introduction

In Study 3 we conducted an online rating study of images from different sub-groups of abstract art paintings. We confined our images to three artists (Piet Mondrian, Jackson Pollock and Mark Rothko) representing three distinct art styles (Neo-plasticism, Action Painting, Color Field Painting) to create relatively homogenous sub-sets that

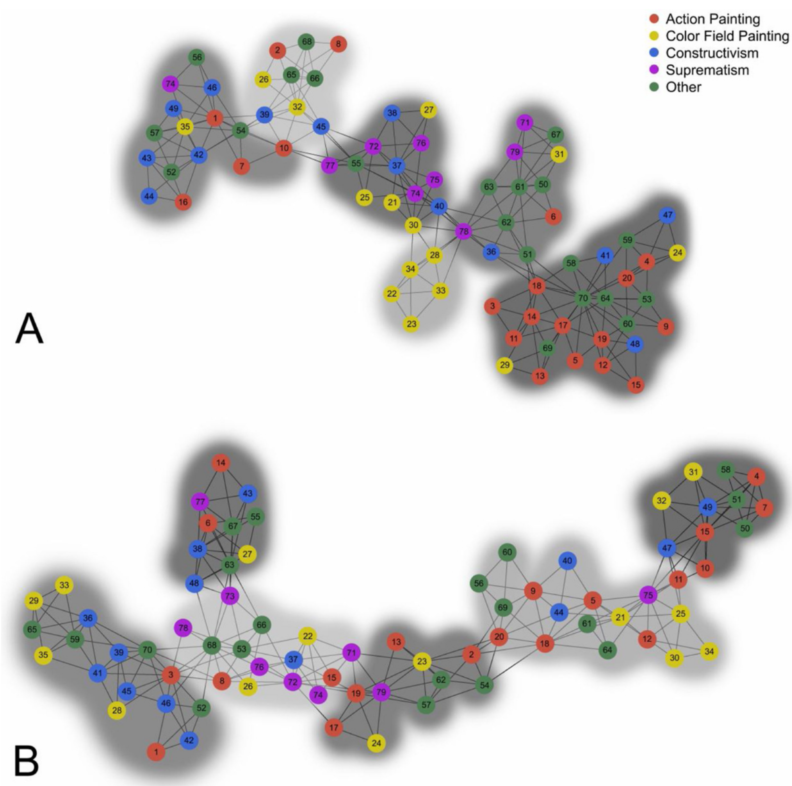

Fig. 2. 2D visualization of the semantic-based (A) and GIP-based (B) networks. Nodes represent the different abstract art painting and edges represent symmetrical, binary relations between nodes. Background hues relate to the different communities detected. Art styles are color-coded. The numbers indicate the painting (Supplemental Table 3).

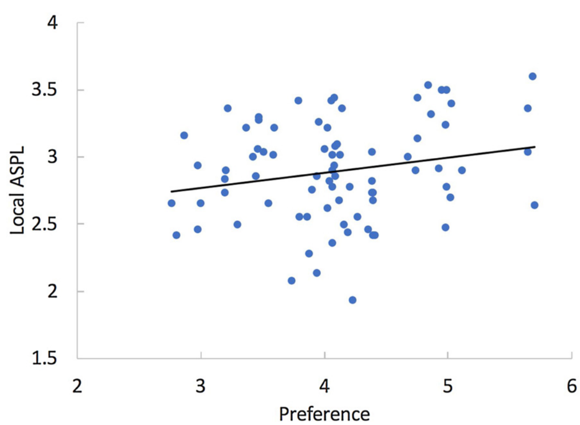

Fig. 3. Scatter plot of local ASPL distances of the 79 abstract art paintings and their preference scores.

Table 2
Distribution of paintings from different art styles on the communities of the semantics network and the GIPs network. Displayed are the numbers of paintings from an art style that were located in the respective cluster (for Semantics and GIPs). The last column shows the standard deviation of the location. Lower values in standard deviation represent a more equal distribution.

Art style	No. of images	C1	C2	C3	C4	C5	C6	SD
Semantic-based Network								
Action Painting	20	1	13	2	4	0	0	4.97
Color Field Painting	15	1	2	2	1	4	5	1.64
Constructivism	14	1	3	2	5	3	0	1.75
Suprematism	9	3	0	0	1	5	0	2.07
Other	21	6	7	3	4	1	0	2.74
GIP-based Network								
Action Painting	20	4	4	3	3	3	5	0.81
Color Field Painting	15	1	2	1	4	2	4	1.37
Constructivism	14	0	2	3	6	1	2	2.07
Suprematism	9	1	0	1	0	6	1	2.26
Other	21	3	3	3	4	3	5	0.84

differ between each other. (A) Neo-plasticism (also *De Stijl*, related to Constructivism; representative artist: Piet Mondrian) follows strict rules of geometrical composition and emphasizes correct form (Mondrian, 1921). (B) Action Painting (a sub-category of Abstract Expressionism; representative artist: Jackson Pollock) focusses on movement (during creation and in depiction) and are overall highly self-similar (Taylor, Micolich, & Jonas, 1999). In contrast, (C) Color Field Painting (also a sub-category of Abstract Expressionism; representative artist: Mark Rothko) is defined by large areas of uninflected hues with only few gradients (Wilkin & Belz, 2007). These areas create the impression of a flat picture.

We examined the relation between preference ratings and GIPs for these sub-groups of images. Based on results of Study 1, we did not expect preference ratings to correlate with GIPs in general (across all abstract art paintingis). Based on Study 2, we predicted the following relations between GIP and preferences for the three sub-groups of paintings: A negative correlation of complexity and a positive correlation with anisotropy in Mondrian paintings, since these paintings emphasize form that is measured by these two values; a positive correlation for self-similarity in Pollocks paintings since self-similarity is regarded as characteristic of these images; and a positive correlation with color values in Rothkos paintings, since these paintings focus on color.

4.2. *Methods*

4.2.1. *Participants*

Twenty participants (21–64 years; *Mean* = 35.5 years, *SD* = 10.0; 5 female) took part in this study. This study was approved by the University of Pennsylvania Institutional Review Board.

4.2.2. *Stimuli*

Stimuli were 90 images of abstract art painting, equally divided (30

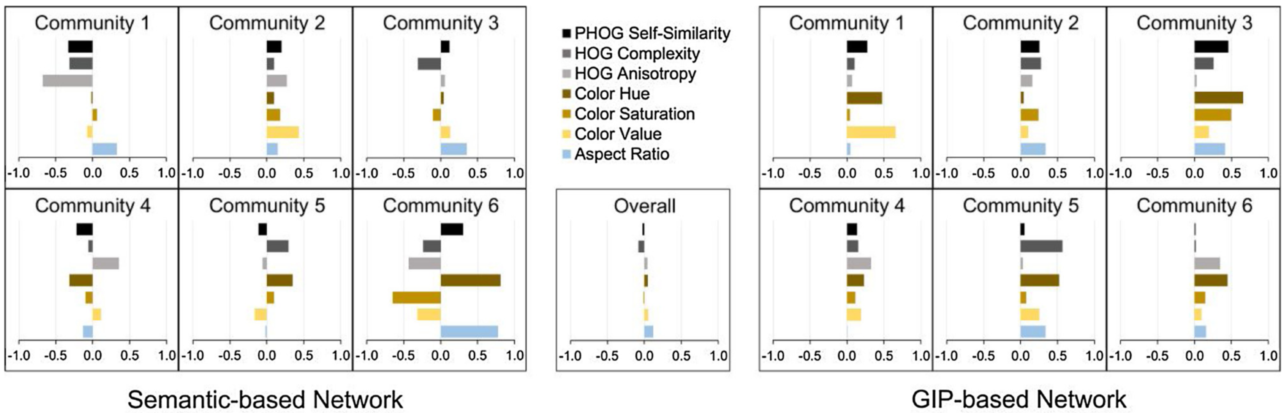

Fig. 4. Displayed are the Pearson's *r* coefficients for the correlation of preference ratings with GIPs over all images and over semantic-based and GIP-based clusters. None of the correlation reached significance after Holm-Bonferroni correction ($p < .01$). We still include this figure to show the tendencies (as compared to no effect over all images).

images) each by Piet Mondrian (Neo-Plasticism), Jackson Pollock (Action Painting), and Mark Rothko (Color Field Painting). Images were presented with a size of 800 pixels (longest side).

4.2.3. Global image properties

The same GIPs as in Study 1 were calculated (self-similarity, complexity, anisotropy, color hue, color saturation, color value, and aspect ratio).

4.2.4. Statistical analysis

We conducted a one-way ANOVA to examine the effect of group on mean ratings for preference. Next, we calculated mean values of GIPs for images from all three groups (Mondrian, Pollock, Rothko). Finally, we calculated Pearson's *r* coefficients for correlations between preference ratings and GIPs for all images and for the three subgroups of images. To control for multiple comparisons, we performed a Holm-Bonferroni correction on the results.

4.2.5. Procedure

In an online experiment via Amazon's Mechanical Turk (Buhrmester, Kwang, & Gosling, 2011), participants rated the images by preference on a scale from 1 (do not like) to 7 (like very much). Images were presented in randomized order and there was no restriction in presentation time.

4.3. Results

First, we investigated the differences in mean preference ratings across the three groups of images. A Group (Mondrian, Pollock, Rothko) One-Way ANOVA on the effect of artist on mean preference ratings revealed a significant effect of Group, $F(2,75) = 63.219$, $p < .001$ (Fig. 5). Post-hoc *t*-test analyses revealed that this effect is driven by a greater preference for Pollock images (Mean = 4.31, SD = .34) compared to the Modrian (Mean = 3.5, SD = .58) and Rothko (Mean = 3.01, SD = .41) images (all *p*'s < .001).

Next, we computed GIP values across the three groups of images. Self-similarity and complexity were higher in Pollock's paintings than in the other groups, while color hue and color saturation were higher in Rothko's paintings than in the other two groups. Finally, Mondrian's paintings stood out by high values of anisotropy as compared to the other two groups (Table 3).

Finally, we investigated the relation between preference ratings and GIPs for the three groups. We found that participants' mean preference ratings correlated positively with self-similarity and complexity, while anisotropy and color (saturation and value) correlated negatively with preference (Fig. 6). For Mondrian paintings, preference ratings correlated negatively with anisotropy. However, in contrast to the overall results, people preferred less self-similar Pollock paintings. This effect was driven by the participant's preference for Pollock's images with self-similarity values similar to those of Mondrian and Pollock paintings (Fig. 7).

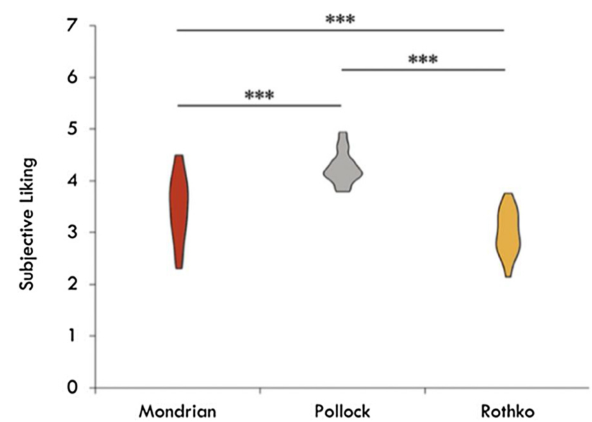

Fig. 5. Average preference ratings of Mondrian, Pollock, and Rothko images; *** = $p < .001$.

Table 3
Mean values of GIPs for images categorized by artist (standard error in parantheses).

	Mondrian	Pollock	Rothko
PHOG Self-Similarity	0.604 (0.146)	0.862 (0.072)	0.585 (0.097)
HOG Complexity	10.174 (5.782)	28.659 (6.674)	2.529 (1.009)
HOG Anisotropy	0.00118 (0.00035)	0.00024 (0.00007)	0.00071 (0.00016)
Color Hue	0.269 (0.135)	0.247 (0.100)	0.378 (0.239)
Color Saturation	0.222 (0.146)	0.250 (0.117)	0.515 (0.232)
Color Value	0.748 (0.116)	0.543 (0.127)	0.537 (0.427)
Aspect Ratio	1.176 (0.297)	0.982 (0.427)	1.174 (0.306)

4.4. Discussion

In Study 3, we examined the relation between preference ratings

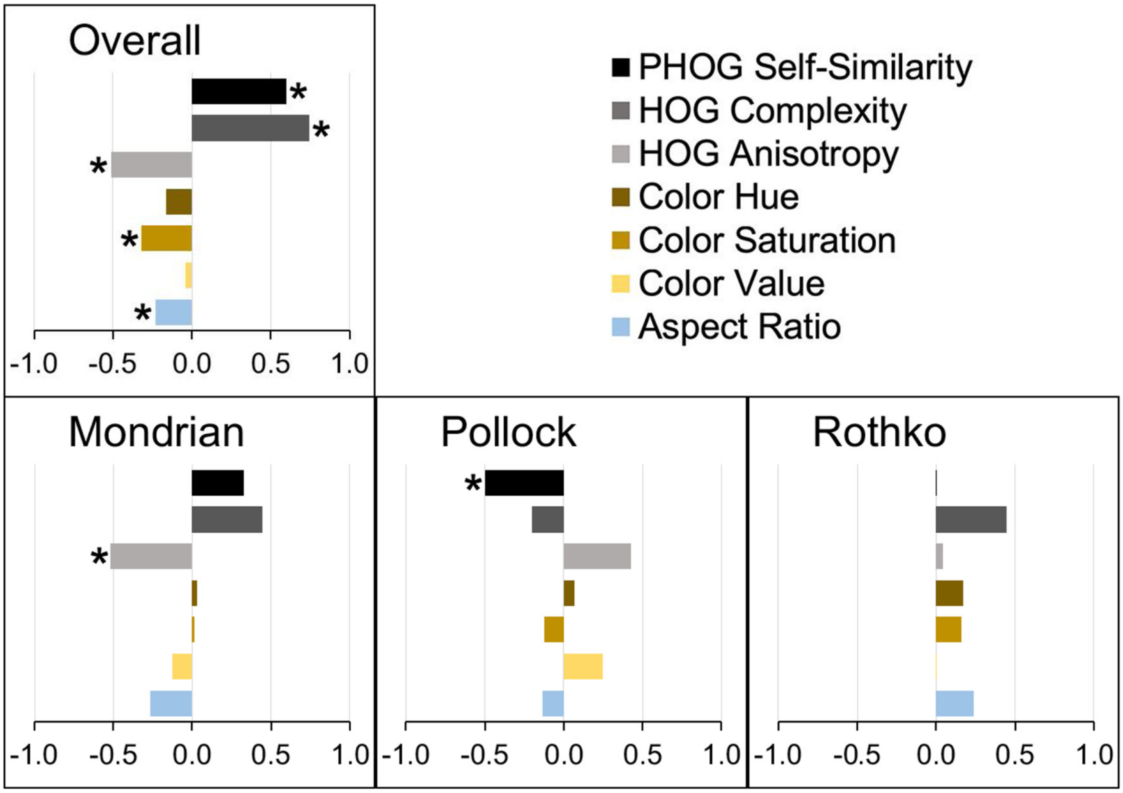

Fig. 6. Pearson's r correlations of preference ratings with GIPs. Displayed are the correlataions for all images and for images from the respective artists. * = $p < .01$ (Holm-Bonferroni corrected).

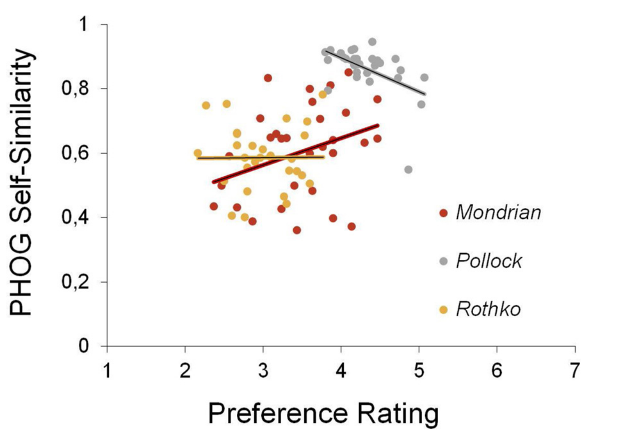

Fig. 7. Single images, as represented by their values on self-similarity, according to their preference values. Mondrian: Pearson's $r = .329$, $p = .076$, 95 % confidence interval $-.034$ to $.649$, Pollock: $r = -.500$, $p < .01$, 95 % confidence interval $-.937$ to $-.185$; Rothko: $r = .006$, $p = .973$, 95 % confidence interval $-.358$ to $.398$.

and GIPs in sub-groups of abstract art paintings. An analysis of GIPs revealed that Pollock‘s paintings are more self-similar than Mondrians and Rothkos paintings. In contrast, color saturation of Mondrian‘s and Pollock‘s paintings are relatively similar, while Rothkos paintings are more highly saturated. Complexity differentiated the painters (Mondrian: medium complexity, Pollock: high complexity, Rothko: low complexity).

Most of the GIP values (self-similarity, complexity, anisotropy, color saturation and aspect ratio) correlated with preference ratings. This observation is in contrast to the findings on abstract art paintings in Study 1. A possible explanation might be the specificity of the paintings from the three artists: Pollocks paintings are –possibly due to cultural reasons – generally preferred and possess on average high values in self-similarity and complexity and low values in anisotropy. Therefore, the effect on preferences of these three GIPs might be driven by this group.

As we predicted, correlations of preference ratings with GIPs differed by artist. Mondrian paintings with lower anisotropy were preferred. Pollock paintings with less self-similarity were preferred (this in in contrast with the finding that over all stimuli, there was a preference for more self-similar images). We did not find any correlations between GIPs and preferences of Rothko's paintings. Our results demonstrate that treating abstract art paintings as a single category obscures potential relation between GIPs and aesthetic judgment for specific artists.

5. General discussion

In the current series of studies, we investigated the relationships between verbal descriptors, GIPs and preferences of abstract art paintings. We did so by combining computational network science methods with empirical approaches. Overall, verbal descriptors related more closely to preferences for abstract art paintings. Furthermore, abstract art paintings can be classified into distinct sub-groups that warrant seperate examination.

In Study 1, we found that people's preference for abstract art paintings did not correlate with GIPs. Such correlations were present for other categories of images. Specifically, people prefered less complex (and less self-similar) magazine covers – which mostly contain only a single image and relatively little printed text (Braun et al., 2013). People also prefered less self-similar images for landscape photographs as reported previously (e.g., Mullin et al., 2017). Similarly, people preferred self-similar and isotropic (low values in anisotropy) house facades. This observation might relate to the hypothesis that people prefer natural-looking patterns (which are self-similar and isotropic) in architecture (Joye, 2007). In face photographs (attractiveness), people prefered images with lower values in self-similarity. Usually, people prefer younger faces, which have fewer wrinkles – and are therefore less self-similar (Menzel et al., 2015). Additionally, we found correlations of preference ratings with GIPs in art categories (e.g., art portraits (beauty and attractiveness): positive with complexity and anisotropy; landscape drawings: positive with complexity, landscape paintings: negative with self-similarity; art installations: positive with self-similarity and complexity). One possibility for why preference ratings and GIPs do not correlate in abstract art paintings is that people's taste for abstract art paintings varies considerably (Mallon et al., 2014). Another possiblity is that abstract art paintings comprise a heterogeneouos group and should be analyzed using better defined sub-groups.

In Study 2 we applied computational network science methods to analyse the relation of verbal descriptors, GIPs, and people's preferences in abstract art paintings (Christensen et al., 2018; Siew et al., 2019). We estimated networks from the same abstract art paintings (Lyssenko et al., 2016) – one based on verbal descriptions (semantic-based network) and the other on GIPs (GIP-based network) of these paintings. We found that a local property of the semantic-based, and not GIP-based, network correlated marginally with preference ratings: The farther (more distinct) an image was from all other images in such a semantic-based network, the more it was preferred. Our computational approach allows us to examine whether these images cluster into sub-communities and if these sub-communities relate to various art styles. The semantic-based network was better than the GIP-based network in clustering abstract art paintings from the same art style. This observation means that subjective perceptions (as reflected by verbal descriptions) of abstract art paintings from the same art style are more similar than their objective GIPs. Following this observation, art styles can be used as sub-groups in the category of abstract art paintings and should be investigated seperately. Perhaps automatic algorithms of image processing could include verbal descriptions, as classification only based on image properties potentially fail. Finally, this study demonstrates the usefulness of applying computational methods to move beyond correlation analysis in examining image based and human-based properties of images.

Based on the results of Study 1 and Study 2, we conducted Study 3 to investigate sub-groups of abstract art paintings (namely paintings from 3 artists) for correlations of preference ratings with GIPs. We selected images from three well-known artists representing distinct styles of abstract art paintings in order to create a controlled set of stimuli. Preference ratings correlated positively with self-similarity for all three artists, but negatively within Pollock's Action Paintings. By contrast, people preferred more isotropic Mondrian paintings. Neo-plasticist paintings of Mondrian emphasize form and the most famous Mondrian paintings (i.e., grid-based paintings created after 1918) are the most isotropic. These famous Mondrian paintings are frequently shown in various contexts and, possibly, participants remembered them. Since familiarity can predict preference (Leder, 2001), it is not surprising that participants preferred isotropic Mondrian paintings.

On the question of why preferences for abstract art paintings vary across participants, we offer provisional answers. Peoples' preferences relate partly to their semantic descriptions of these paintings. Furthermore, preferences are better predicted by GIPs if abstract art paintings are grouped by style. We speculate that people have a specific taste in art (e.g., some prefer Mondrians neo-plasticist paintings over Pollocks drip paintings, for others it is the other way around). Within art styles, specific GIPs are preferred. However, because semantic descriptors predict general preference ratings and a combination of GIPs does not, we speculate that GIPs – while being narrowly relevant to preferences within a specific art style – cannot be a general explanation for people's preferences for abstract art."Our findings resonate with a similar a debate in computational semantics; whether textual-based computational methods of semantics predict human behavior (Mandera, Keuleers, & Brysbaert, 2017, 2019, Hutchison, Balota, Cortese, & Watson, 2008; Kenett, 2018; Mandera, Keuleers, & Brysbaert, 2015; Vankrunkelsven, Verheyen, Storms, & De Deyne, 2018). Such textual-based methods compute multidimensional semantic vectors based on co-occurrence statistics from textual corpora, while behavioral-based methods compute relations between concepts based on linguistic output (Kenett, 2018, 2019). Eventhough textual-based methods capture some aspects of semantic similarity and memory retrieval (Griffiths, Steyvers, & Firl, 2007; Mandera et al., 2017), behavioral-based methods seem to outperform the textual-based methods in predicting human behavior (Kenett et al., 2017; Vankrunkelsven et al., 2018).

6. Limitations

Although we aimed to investigate a representative subset of abstract art paintings in Study 2, we still based our analysis on availability of artworks. Therefore, a generalization of the results with larger and more varied abstract art paintings samples would be useful. In Study 3, we did not find any significant correlations of GIPs with preference ratings in Rothko paintings. This could indicate that 30 images might be too few for such a kind of studies.

7. Summary

In sum, we conducted a series of studies examining the relation between verbal descriptors, GIPs, and preferences for abstract art paintings. Our results demonstrate that applying quantitative methods from network science can be fruitful in the study of aesthetics. Furthermore, we demonstrate how verbal (semantic) descriptions should be taken into account to divide abstract art paintings into sub-groups.

Acknowledgments

We thank Nathalie Lyssenko for preprocessing of the data. This work has been funded by the German Research Council, grant number HA 6850/1-1 (to GUHL) and the Smith Family Fund.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.actpsy.2019.102936.

References

Amirshahi, S. A., Denzler, J., & Redies, C. (2013). Jenaesthetics–a public dataset of paintings for aesthetic research. *Paper Presented at the European Conference on Computer Vision*.

Amirshahi, S. A., Koch, M., Denzler, J., & Redies, C. (2012). PHOG analysis of self-similarity in aesthetic images. *Paper Presented at the Human Vision and Electronic Imaging XVII*.

Augustin, M. D., Wagemans, J., & Carbon, C.-C. (2012). All is beautiful? Generality vs. specificity of word usage in visual aesthetics. *Acta Psychologica, 139*(1), 187–201.

Barabási, A.-L. (2016). *Network science.* Cambridge University Press.

Baronchelli, A., Ferrer-i-Cancho, R., Pastor-Satorras, R., Chater, N., & Christiansen, M. H. (2013). Networks in cognitive science. *Trends in Cognitive Sciences, 17*(7), 348–360.

Bassett, D. S., Wymbs, N. F., Porter, M. A., Mucha, P. J., Carlson, J. M., & Grafton, S. T. (2011). Dynamic reconfiguration of human brain networks during learning. *Proceedings of the National Academy of Sciences, 108*(18), 7641–7646.

Betzel, R. F., Medaglia, J. D., Papadopoulos, L., Baum, G. L., Gur, R., Gur, R., et al. (2017). The modular organization of human anatomical brain networks: Accounting for the cost of wiring. *Network Neuroscience, 1*(1), 42–68.

Bonacich, P. (2007). Some unique properties of eigenvector centrality. *Social Networks, 29*(4), 555–564.

Bonacich, P., & Lloyd, P. (2001). Eigenvector-like measures of centrality for asymmetric relations. *Social Networks, 23*(3), 191–201.

Borgatti, S. P. (2005). Centrality and network flow. *Social Networks, 27*(1), 55–71.

Borgatti, S. P., & Everett, M. G. (2000). Models of core/periphery structures. *Social Networks, 21*(4), 375–395.

Borge-Holthoefer, J., & Arenas, A. (2010). Semantic networks: Structure and dynamics. *Entropy, 12*(5), 1264–1302.

Borodkin, K., Kenett, Y. N., Faust, M., & Mashal, N. (2016). When pumpkin is closer to onion than to squash: The structure of the second language lexicon. *Cognition, 156*, 60–70.

Bosch, A., Zisserman, A., & Munoz, X. (2007). Representing shape with a spatial pyramid kernel. *Paper Presented at the Proceedings of the 6th ACM International Conference on*

Image and Video Retrieval.
Böthig, A. M., & Hayn-Leichsenring, G. U. (2017). Taste in art—Exposure to histological stains shapes abstract art preferences. *i-Perception, 8*(5), 2041669517736073.
Braun, J., Amirshahi, S. A., Denzler, J., & Redies, C. (2013). Statistical image properties of print advertisements, visual artworks and images of architecture. *Frontiers in Psychology, 4*, 808.
Brinkmann, H., Commare, L., Leder, H., & Rosenberg, R. (2014). Abstract art as a universal language? *Leonardo, 47*(3), 256–257.
Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's mechanical turk a new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science, 6*(1), 3–5.
Cattaneo, Z., Lega, C., Ferrari, C., Vecchi, T., Cela-Conde, C. J., Silvanto, J., et al. (2015). The role of the lateral occipital cortex in aesthetic appreciation of representational and abstract paintings: A TMS study. *Brain and Cognition, 95*, 44–53.
Christensen, A. P., Kenett, Y. N., Aste, T., Silvia, P. J., & Kwapil, T. R. (2018). Network structure of the Wisconsin Schizotypy Scales–Short forms: Examining psychometric network filtering approaches. *Behavior Research Methods, 50*(6), 2531–2550.
Dalal, N., & Triggs, B. (2005). Histograms of oriented gradients for human detection. *Paper Presented at the Computer Vision and Pattern Recognition, 2005*.
Ebner, N. C., Riediger, M., & Lindenberger, U. (2010). FACES—A database of facial expressions in young, middle-aged, and older women and men: Development and validation. *Behavior Research Methods, 42*(1), 351–362.
Epskamp, S., Maris, G., Waldorp, L. J., & Borsboom, D. (2015). *Network psychometrics, handbook of psychometrics.* New York, NY: Wiley.
Fernie, E. (1995). *Art history and its methods: A critical anthology.* London, UK: Phaidon.
Fortunato, S. (2010). Community detection in graphs. *Physics Reports, 486*(3–5), 75–174.
Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry, 40*(1), 35–41.
Griffiths, T. L., Steyvers, M., & Firl, A. (2007). Google and the mind: Predicting fluency with PageRank. *Psychological Science, 18*(12), 1069–1076.
Hayn-Leichsenring, G. U., Lehmann, T., & Redies, C. (2017). Subjective ratings of beauty and aesthetics: Correlations with statistical image properties in Western oil paintings. *i-Perception, 8*(3), 2041669517715474.
Hills, T. T., Maouene, M., Maouene, J., Sheya, A., & Smith, L. (2009). Longitudinal analysis of early semantic networks: Preferential attachment or Preferential acquisition? *Psychological Science, 20*(6), 729–739.
Hutchison, K. A., Balota, D. A., Cortese, M. J., & Watson, J. M. (2008). Predicting semantic priming at the item level. *The Quarterly Journal of Experimental Psychology, 61*(7), 1036–1066.
Jacobsen, T., Buchta, K., Köhler, M., & Schröger, E. (2004). The primacy of beauty in judging the aesthetics of objects. *Psychological Reports, 94*, 1253–1260.
Joye, Y. (2007). Architectural lessons from environmental psychology: The case of biophilic architecture. *Review of General Psychology, 11*(4), 305–328.
Kenett, Y. N. (2018). Going the extra creative mile: The role of semantic distance in creativity – Theory, research, and measurement. In R. E. Jung, & O. Vartanian (Eds.). *The Cambridge handbook of the neuroscience of creativity* (pp. 233–248). New York, NY: Cambridge University Press.
Kenett, Y. N. (2019). What can quantitative measures of semantic distance tell us about creativity? *Current Opinion in Behavioral Sciences, 27*, 11–16.
Kenett, Y. N., Anaki, D., & Faust, M. (2014). Investigating the structure of semantic networks in low and high creative persons. *Frontiers in Human Neuroscience, 8*(407), 1–16.
Kenett, Y. N., & Faust, M. (2019). A semantic network cartography of the creative mind. *Trends in Cognitive Sciences, 23*(4), 271–274.
Kenett, Y. N., Levi, E., Anaki, D., & Faust, M. (2017). The semantic distance task: Quantifying semantic distance with semantic network path length. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 43*(9), 1470–1489.
Lancichinetti, A., & Fortunato, S. (2009). Community detection algorithms: A comparative analysis. *Physical Review E, 80*(5), 056117.
Lancichinetti, A., & Fortunato, S. (2012). Consensus clustering in complex networks. *Scientific reports, 2*, 336.
Leder, H. (2001). Determinants of preference: When do we like what we know? *Empirical Studies of the Arts, 19*(2), 201–211.
Lyssenko, N., Redies, C., & Hayn-Leichsenring, G. U. (2016). Evaluating abstract art: Relation between term usage, subjective ratings, image properties and personality traits. *Frontiers in Psychology, 7*, 973.
Mallon, B., Redies, C., & Hayn-Leichsenring, G. U. (2014). Beauty in abstract paintings: Perceptual contrast and statistical properties. *Frontiers in Human Neuroscience, 8*, 161.
Mandera, P., Keuleers, E., & Brysbaert, M. (2015). How useful are corpus-based methods for extrapolating psycholinguistic variables? *The Quarterly Journal of Experimental Psychology, 8*, 1628–1642.
Mandera, P., Keuleers, E., & Brysbaert, M. (2017). Explaining human performance in psycholinguistic tasks with models of semantic similarity based on prediction and counting: A review and empirical validation. *Journal of Memory and Language, 92*, 57–78.
Marković, S., & Radonjić, A. (2008). Implicit and explicit features of paintings. *Spatial Vision, 21*(3), 229–259.
McManus, I. C. (1980). The aesthetics of simple figures. *British Journal of Psychology, 71*(4), 505–524.
Menzel, C., Hayn-Leichsenring, G. U., Langner, O., Wiese, H., & Redies, C. (2015). Fourier power spectrum characteristics of face photographs: Attractiveness perception depends on low-level image properties. *PloS One, 10*(4), e0122801.
Mondrian, P. (1921). Le neo-plasticisme (principle general de l'equivalence plastique). *De Stijl, 1921*, 18–19 February.
Mullin, C., Hayn-Leichsenring, G. U., Redies, C., & Wagemans, J. (2017). The gist of beauty: An investigation of aesthetic perception in rapidly presented images. *Electronic Imaging, 2017*(14), 248–256.
Newman, M. E. J. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences USA, 103*(23), 8577–8582.
Redies, C., Amirshahi, S. A., Koch, M., & Denzler, J. (2012). PHOG-derived aesthetic measures applied to color photographs of artworks, natural scenes and objects. *Paper Presented at the European Conference on Computer Vision*.
Redies, C., Brachmann, A., & Hayn-Leichsenring, G. U. (2015). Changes of statistical properties during the creation of graphic artworks. *Art & Perception, 3*(1), 93–116.
Redies, C., Hasenstein, J., & Denzler, J. (2007). Fractal-like image statistics in visual art: Similarity to natural scenes. *Spatial Vision, 21*(1), 137–148.
Rubinov, M., & Sporns, O. (2010). Complex network measures of brain connectivity: Uses and interpretations. *NeuroImage, 52*(3), 1059–1069.
Russell, P. A. (2000). Testing the aesthetic significance of the golden-section rectangle. *Perception, 29*(12), 1413–1422.
Schulz, K., & Hayn-Leichsenring, G. U. (2017). Face attractiveness versus artistic beauty in art portraits: A behavioral study. *Frontiers in Psychology, 8*, 2254.
Shannon, P., Markiel, A., Ozier, O., Baliga, N. S., Wang, J. T., Ramage, D., et al. (2003). Cytoscape: A software for integrated models of biomolecular interaction networks. *Genome Research, 13*(11), 2498–2504.
Siew, C. S. Q., Wulff, D. U., Beckage, N. M., & Kenett, Y. N. (2019). Cognitive network science: A review of research on cognition through the lens of network representations, processes, and dynamics. *Complexity, 2019*, 24.
Smith, A. R. (1978). Color gamut transform pairs. *ACM Siggraph Computer Graphics, 12*(3), 12–19.
Steyvers, M., & Tenenbaum, J. B. (2005). The large scale structure of semantic networks: Statistical analysis and a model of semantic growth. *Cognitive Science, 29*(1), 41–78.
Taylor, R. P., Micolich, A. P., & Jonas, D. (1999). Fractal analysis of pollock's drip paintings. *Nature, 399*(6735), 422.
Tumminello, M., Aste, T., Di Matteo, T., & Mantegna, R. N. (2005). A tool for filtering information in complex systems. *Proceedings of the National Academy of Sciences, 102*(30), 10421–10426.
van Borkulo, C. D., Boschloo, L., Borsboom, D., Penninx, B. W. J. H., Waldorp, L. J., & Schoevers, R. A. (2015). Association of symptom network structure with the course of depression. *JAMA Psychiatry, 72*(12), 1219–1226.
van Wijk, B. C. M., Stam, C. J., & Daffertshofer, A. (2010). Comparing brain networks of different size and connectivity density using graph theory. *PLoS ONE, 5*(10), e13701.
Vankrunkelsven, H., Verheyen, S., Storms, G., & De Deyne, S. (2018). Predicting lexical norms: A comparison between a word association model and text-based word cooccurrence models. *Journal of Cognition, 1*(1), 45.
Vessel, E. A., & Rubin, N. (2010). Beauty and the beholder: Highly individual taste for abstract, but not real-world images. *Journal of Vision, 10*(2), 18.
Vitevitch, M. S., Chan, K. Y., & Goldstein, R. (2014). Insights into failed lexical retrieval from network science. *Cognitive Psychology, 68*, 1–32.
Vitevitch, M. S., Chan, K. Y., & Roodenrys, S. (2012). Complex network structure influences processing in long-term and short-term memory. *Journal of Memory and Language, 67*(1), 30–44.
Vitevitch, M. S., Goldstein, R., & Johnson, E. (2016). Path-length and the misperception of speech: Insights from network science and psycholinguistics. In A. Mehler, A. Lücking, S. Banisch, P. Blanchard, & B. Job (Eds.). *Towards a theoretical framework for analyzing complex linguistic networks* (pp. 29–45). Berlin, Heidelberg: Springer Berlin Heidelberg.
Wilkin, K., & Belz, C. (2007). *Color as field: American painting, 1950–1975.* Yale University Press.