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Cognitive Psychology

Associating With Art: A Network Model of Aesthetic Effects

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In recent years, understanding psychological constructs as network processes has gained considerable traction in the social sciences. In this paper, we propose the aesthetic effects network (AEN) as a novel way to conceptualize aesthetic experience. The AEN represents an associative process where having one association leads to the next association, generating an overall aesthetic experience. In art theory, associations of this kind are referred to as *aesthetic effects*. The AEN provides an explicit account of a specific cognitive process involved in aesthetic experience. We first outline the AEN and discuss empirical results (Study 1, *N*=255) to explore what can be gained from this approach. Second, in Study 2 (*N*=133, pre-registered) we follow calls in the literature to substantiate network theories by using an experimental manipulation, and found evidence in favor of the AEN over other alternatives. The AEN provides a basis for future studies that can apply a network perspective to different aesthetic experiences and processes. This perspective takes a process-based approach to aesthetic experience, where aesthetic experience is represented as an active interaction between viewer and artwork. If we want to understand how people experience art, it is central to know why people have different experiences with the same artworks, and, also, why people have similar experiences when looking at different artworks. Our proposed network perspective offers a new way to approach and potentially answer these questions.

1. Introduction

Aesthetic experiences are complex experiences that unfold over time and assume a strong relation between features in artworks and their effects on the beholder. But how does this actually happen? A key concept is *aesthetic effect* which, since the 18th century, has been used in art literature to explain responses to artworks (Brinkmann et al., 2018; Schnackertz, 2010). The assumption is that works of art produce specific aesthetic effects in viewers that are caused by single elements, such as a red causing a sensation of warmth, or a horizontal line causing a quiet sensation. For example, Franz Marc described colors in a letter to August Macke as follows: "Blue is the male principle, astringent and spiritual. Yellow is the female principle, gentle, gay and sensual. Red is matter, brutal and heavy and always the color to be opposed and overcome by the other two" (1964, p. 28). Similar descriptions can be found for lines. Kandinsky, for example, postulated: "The same thing can with complete justification be said about the horizontal and the vertical - low and high. The former is lying, the latter is standing, walking, moving about, finally climbing upward. Supporting - growing. Passive - active. Relatively: feminine - masculine" (Kandinsky, 1947, p. 63).

Note that aesthetic effects are used to describe how the artwork *appears* to the viewer rather than the viewers direct experience. The viewer does not feel "gay" when looking at yellow, nor are they "lying" when looking at horizontal lines. Rather, the yellow appears "gay" to the viewer, and, similarly, horizontal lines are seen by the viewer as "lying". Therefore, these aesthetic effects can best be translated as *associations* in psychological nomenclature. Aesthetic effects are often described as co-occurring—multiple effects such as warmth and quiet are simultaneously caused by the same artwork—but their connection to each other is rarely made explicit.

In this paper, we propose a novel way to conceptualize these effects by explicitly connecting them to each other. In stark contrast to prior work, we conceive these effects as an associative process of direct relationships between aesthetic effects by utilizing a network approach.

We first describe the theoretical model employed by previous research to highlight the contrast with our proposition of an associative process. Second, we introduce our

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theoretical model, the aesthetic effects network (AEN), and discuss the results of an empirical study (Study 1) that was conducted to explore what information can be gained from taking this approach. Third, we discuss the results of a preregistered follow-up study (Study 2) that provides evidence for the AEN over other explanations.

1.1. Theoretical Background

A major body of previous empirical work on aesthetic effects consists of artistic research (Borgdorff, 2009, 2012)—in which artists experiment with their art in an attempt to create a specific effect—rather than scientific research (Brinkmann et al., 2018). The few scientific studies examining associations with art, such as Takahashi (1995), relied on Osgood et al.'s EPA model (Osgood et al., 1957), which was developed to capture semantic space or meaning in three latent factors: Evaluation, Potency, and Activity.[1] To measure meaning, Osgood et al. proposed a semantic differential (or bipolar scale), which uses two opposing adjectives such as happy–sad, active–passive, or strong–weak.

For aesthetics that means that, when people look at an artwork, they will perceive a certain level of Activity in the artwork, which will consequently lead to a related score in the corresponding indicator. For example, if the Activity is high, a person will rate the painting as *lively* rather than *still*. In this model, relationships between aesthetic effects are due to a common cause: if *active* and *lively* are correlated this is because they are both caused by the latent factor of Activity.

In our view, relationships between aesthetic effects should be seen as direct associations between one aesthetic effect and another; this presupposes a level of causality where the aesthetic effects can cause each other. Thus, the main difference between the common cause perspective (EPA model) and our proposed AEN model (see 1.2 for details) is the conceptualization and interpretation of relationships between aesthetic effects. In the EPA model, this relation exists because they belong to the same factor. In the AEN, these are interpreted as direct relationships. The conceptual notions behind the EPA and AEN model are illustrated in Figure 1.

Approaches such as the EPA model represent a relationship between artwork and viewer, where the artwork can inspire aesthetic effects in the viewer who is a passive receiver. The AEN model claims a more active role of the viewer. Though the initial stimulation comes from the artwork, the viewer can freely associate throughout the AEN:

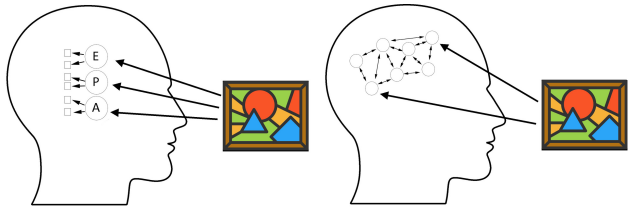

Figure 1. Conceptual model of how an artwork can influence a person in the Evaluation Potency Activity model (left) and a network model (right)

this process constitutes an aesthetic experience.[2] This is analogous to semantic networks such as word associations that have been widely described as network structures (De Deyne & Storms, 2008; Steyvers & Tenenbaum, 2005), where the activation of one word (e.g., "love") leads to the activation of another word (e.g., "heart"). These networks have been used to predict performance in memory retrieval tasks and explain various priming and interference phenomena (Collins & Loftus, 1975; Nelson et al., 1998). One especially relevant concept in this context is that of "spreading activation" (Anderson, 1983) which holds that, as one node in the network is "activated", this activation can then spread throughout the network. We propose that a similar process would underly the AEN. Note that a full investigation on models from cognitive psychology and how they relate to the topic at hand is outside the scope of the current paper. As a first step, we decided to exclude this since we are already aiming to bridge art history, empirical aesthetics, and network modeling. Nonetheless, as this approach develops, it should consider the work done in cognitive psychology in more detail.

Finally, note that the main difference between the EPA and the AEN model is theoretical (see also our rationale for Study 2 below) rather than a distinction between factor analytic and network analysis. Our aim with the current paper is to introduce this new theoretical point of view, rather than to introduce a new methodology. As noted above and illustrated in Figure 1, the theoretical difference focuses around the interpretation of the interrelations between aesthetic effects. Finally, we view the current paper as a first step into this new theoretical direction, while at the same time realizing that much additional work is needed to substantiate this theory. Since this perspective on the future is

1 It is important to note here that in the conception of Osgood et al. (1957) the factors are causes and not summaries of the items. They note that there is no definite set of items to test for the EPA model, the specific items chosen depend on the specific subject matter, however, that "Standardization, and hence comparability, lies in the allocation of concepts to a common semantic space defined by a common set of general factors, despite variability in the particular concepts and scales employed". (p.76)

2 The idea that an aesthetic experience includes an associative process can be traced back to founding father of empirical aesthetics Gustav Theodor Fechner and his 1866 article "The Aesthetic Association Principle" (*Das Associationsprincip in der Aesthetik*), recently translated for the first time to English by Ortlieb et al. (2020). Though a full discussion is beyond the scope of the current paper, one specific part of Fechner's text is particularly relevant here: Fechner writes (as translated by Ortlieb et al., 2020): "If we hit a taut fabric in some spot—our imagination is comparable to such a fabric—the whole fabric will vibrate, but especially those parts that are closest to the spot we have hit or that are connected with it by the strongest threads." (p.8). This seems analogous to our AEN, if we substitute "fabric" with "network", "spot" with "node" and "threads" by "edges".

thus also a significant contribution of the current paper, we address this at length in the Limitations and Future Directions section at the end of the paper.

1.2. Aesthetic effects network (AEN)

1.2.1. Structure

We propose to model the associative process between aesthetic effects as a statistical network. Networks consist of *nodes* and *edges*. *Nodes* represent entities and *edges* represent connections between these entities. This general concept is illustrated by the notion of "six degrees of separation", the idea that any two random people on earth are six or fewer acquaintances apart, originally tested empirically by Travers & Milgram (1969). This is an example of a social network where nodes represent people, for example Harry and Sally, and edges represent relationships between them. Thus, if Harry and Sally know each other, there will be an edge connecting the node of Harry to the one of Sally.

In the AEN, aesthetic effects (*active*, *lively*, etc.) are represented by nodes. Associations between the aesthetic effects are represented as edges. Thus, if *active* is associated with *lively*, there will be an edge connecting the nodes. What "associated" in the previous sentence means is not trivial: in a social network, we can simply observe if people are friends (e.g., on Facebook); in the social sciences, we require psychometric models to estimate such relations.

We propose that in the AEN, the edges will not be binary (i.e., either present or absent) but are more appropriately modelled as continuous, representing the strength of associations. In addition, *active* and *lively* can be positively associated (i.e., the more active, the more lively) or negatively associated (i.e., the more active, the less lively). In our case, we conceptualize these edges as partial correlations because we are interested in the shared unique relations among aesthetic effects partialling out all other aesthetic effects. This means that the variables are dependent conditional on all other items in the network (for an overview of these models, see Epskamp & Fried, 2018).

1.2.2. On the importance of the stimulus

Aesthetic effects occur as a reaction to a stimulus much like attitude networks (Dalege et al., 2016) that represent attitudes towards a specific object or person—without president Trump, there is no attitude towards president Trump. We term such networks *stimulus-bound* since they only exist as a reaction towards a stimulus, in contrast to e.g., social networks which are not stimulus-bound. Although separating these out may in some cases be difficult, the main difference is that stimulus-bound networks require elicitation by the stimulus to be observable while non stimulus-bound networks do not.

The stimulus in attitude or aesthetic networks exists outside of the network itself in the *external field* (Borsboom, 2017), denoting factors that can influence nodes inside the network from the outside (cf. Figure 1). Thus, the stimulus may influence one (or multiple) nodes in the network but is not itself a part of the network and, therefore, not represented in the network by a node. In the case of stimulus-bound networks, we propose that the stimulus would be seen as the common cause—as such, the full model can be conceptualized as a hybrid model (Fried & Cramer, 2017) which is a mixture of a network model and a common cause model—meaning that the stimulus activates certain (not necessarily all) nodes in the network. For example, if Sally perceives a painting, this painting can cause the association of *active* in her. Since the association *active* is a node in the network, the activation can then spread from there throughout the network (see Figure 1). This also opens up the possibility for a network approach to individual differences in aesthetic experience. We will return to this issue in the Limitations and Future Directions section.

2. Study 1

Here we report the results of an empirical study to put forth a preliminary account of the structure of the relationships between different aesthetic effects.

2.1. Participants

We surveyed 255 voluntary participants (92 male, 160 female, 2 identifying as other, 1 unreported, mean age = 20.73, SD = 3.73) in a first-year psychology lecture. We collected a convenience sample of participants with the aim of recruiting as many participants as possible in a single session. All experiments of the present paper were carried out in German, in accordance with the Declaration of Helsinki, and after approval by the local ethical committee of the University of Vienna.

2.2. Materials

2.2.1 Aesthetic Effects

To measure aesthetic effects, we included 14 items. Each item was a semantic differential, where each aesthetic effect was represented by opposite pairs as poles of the scale, for example: warm–cold. The choice of the semantic differential format and of our specific word pairs was based on a recent historical analysis of the most frequently used terms for aesthetic effects in art literature (Brinkmann et al., 2018). We used these pairs of terms: negative–positive, passive–active, lively–still, happy–sad, aggressive–peaceful, soft–hard, warm–cold, heavy–light, smooth–rough, bodily–spiritual, masculine–feminine, intrusive–cautious.[3] In addition, we included dislike–like and uninteresting–interesting because they are outcome variables of aesthetic experience that are widely considered as relevant and important by psychologists as shown by, for example, the in-

3 All word pairs were presented in German. Original versions were (in same order as above): negativ–positiv, passiv–aktiv, lebhaft–ruhig, fröhlich–traurig, aggressiv–friedlich, weich–hart, warm–kalt, schwer–leicht, sanft–grob, körperlich–geistig, maskulin–feminin, aufdringlich–zurückhaltend, gefällt mir nicht–gefällt mir, uninteressant–interessant.

Table 1. Artworks used in the study

Artist	Title	Shorthand Title	Year	Collection
Paul Klee	Zeichen in Gelb/ Sign in Yellow	Klee Yellow	1937	Foundation Beyeler, Riehen/Basel
Paul Klee	Blick aus Rot/ Be aware of Red	Klee Red	1937	Zentrum Paul Klee, Bern
Wassily Kandinsky	Regungen/ Impulses	Kandinsky Albertina	1928	Albertina Vienna – permanent loan basis, Collection Forberg
Wassily Kandinsky	Untitled	Kandinsky Pompidou	1934	Centre Pompidou, Paris
Richard Mortensen	Øvelsesstykker/ Exercise pieces	Mortensen Pink	1922	Private Collection – sold by Bruun Rasmussen Auctioneers, 6. August 1992, lot 728
Richard Mortensen	Øvelsesstykker/ Exercise pieces	Mortensen Orange	1922	Private Collection – on sale at Bruun Rasmussen Auctioneers, 20. July 1992, lot 729
Joan Mirò	Untitled	Miro	1961	Yvon Taillandier, Pierre Matisse Gallery, cat raissonnee: 292
Fritz Winter	Siebdruck 6/ Silkscreen 6	Winter	1950	Galleri MDA, Sweden, Helsingborg

fluential Pleasure-Interest Model of Aesthetic Liking by Graf & Landwehr (2015) and the seminal work by Daniel Berlyne (1974).

In each case, the left term was represented by 1 and the right term by 7. Left term and right term are here used to refer to the opposite sides of the dimension such as "warm-cold", in this case warm would be referred to by 1 and cold by 7. The specific wording of questions for each scale was as follows, "This image appears … warm/cold" (In German: "Dieses Bild wirkt … warm/kalt"). For liking the question was rephrased to "I like/I do not like this image" (in German: "Dieses Bild … Gefällt mir/Gefällt mir nicht") in order to stay grammatically correct (please note that in German the grammar between liking and the other scales is much more similar than in English).

2.2.2. Stimuli

As stimuli we used 8 abstract artworks by 5 different artists. Image choice was based on Brinkmann et al. (2018) and Specker et al. (2020); all images represented work by artists that can be directly related to art historical theories on aesthetic effects. All image information and their shorthand titles can be found in Table 1. For ease of reading we chose shorthand titles for each of them (see third column) to be used throughout the text and in all figures and tables. We chose a relatively homogenous set of artworks, because we aimed to average across artworks to derive a general network structure. Data on no other artworks was collected, i.e., we did not perform a sub-selection of specific artworks for the purpose of this paper.

2.3. Procedure

The study took place during a first-year psychology lecture. All images were projected against a black background by use of a projector. Thus, image presentation was consistent across participants. Participants were instructed to first look at each image, let it make an impression on them, and then to rate the image on the 14 aesthetic effects within a total viewing time of 75 seconds for each image. After each image, a blank black screen was shown for 5 seconds before moving on to the next image. Responses could be given during the entire viewing time (75 + 5 sec). Ratings could be made either with pen and paper or a digital answering option (tablet, PC, and phone). Pen and paper responding (N = 127) was partly randomized: each participant had the same question order for each image, but the question order was different for each image. For digital responding (N = 128), the question order was random for both images and participants. All scales were presented on one page.

2.3.1. Network Estimation

We employed a 3-step analytic strategy similar to Rhemtulla et al. (2016; for a similar, more recent example see Fried et al., 2018). In their study, Rhemtulla et al. (2016) used network analysis to compare the interrelation of symptoms in six different datasets of patients with different substance abuse disorders. To do this, they first estimated a symptom network for each substance abuse disorder dataset. Then they estimated a global network across all datasets to understand what a general network of substance abuse symptoms would look like. Finally, they estimated a variability network to assess the variability of the edges across the six individual substance abuse disorder networks. Though we are not at all examining mental disorders, our aims in the current study are comparable: we want to compare the interrelation of aesthetic effects for multiple artworks and estimate a global network of aesthetic effects. A variability analysis then adds to our understanding of how associations between the aesthetic effects differ depending on which artwork people are viewing. Therefore, we followed the approach of Rhemtulla et al. (2016) and performed three analyses. In contrast to Rhemtulla et al. (2016), and based on Fried et al. (2018), we only interpret the centrality in terms of *expected influence*, because

strength takes absolute values and thus does not take negative edges into account, and *betweenness* and *closeness* centrality are often unreliable (e.g., Epskamp et al., 2018). How to interpret centrality statistics (i.e. inference) is being actively debated in the literature (Bringmann et al., 2019; Christensen & Golino, 2020; Hallquist et al., 2019). Here, we use the expected influence statistic, since it provides a measure of how connected one node is to the network. Our interpretation is that more connected nodes are more likely to influence other nodes in the network (as is assumed by accounts of spreading activation, discussed above). This inference is based on our theoretical views, and requires further corroboration before any strong conclusions can be drawn. In addition, we estimated the accuracy and stability for the individual networks (following Epskamp et al., 2018)—corresponding plots can be found in the Supplementary Material. Note that these procedures cannot be applied to the global network as the global network is not estimated in and of itself but is an average over the estimates of the individual networks. All centrality measures were standardized. All analyses were performed in R using the "*qgraph*" package (Epskamp et al., 2012) implementing a Gaussian graphical model (GGM), a network in which edges connecting aesthetic effects represent estimates of partial correlations, including a graphical lasso regularization. In the GGM, edges can be understood as conditional dependence relations among aesthetic effects: If two aesthetic effects are connected in the resulting graph, they are dependent after controlling for all other symptoms. If no edge emerges, aesthetic effects are conditionally independent. Regularization involves estimating a statistical model with an extra penalty for model complexity (Epskamp & Fried, 2018). This procedure leads to networks that are sparse and constrain many of the small coefficients to zero. This means that edges that are likely to be spurious are removed from the model, leading to networks that are simpler to interpret. Using the graphical lasso to estimate a GGM improves network estimates and leads to a sparse network that describes the data parsimoniously. We used the method of regularization outlined in Epskamp & Fried (2018), using the default setting of the gamma parameter of 0.5. For the global network, we then averaged each edge across the eight separate artwork networks. The GGM with regularization represents the current state-of-the-art for ordinal or continuous data. Note that, while the model aims to map conditional dependence relations, causal claims do not follow from the statistical model, which is why Figure 2 (see below) does not include arrows. The final dataset used for the network analyses and the corresponding code can be found on the Open Science Framework (OSF): https://osf.io/zqxbm/.

3. Results

3.1. Global network

We start with the interpretation of the global network of aesthetic effects (averaged across all 8 individual networks), shown in Figure 2. The corresponding centrality plot is shown in Figure 3. The individual networks and their comparison follow afterwards.

The general network of aesthetic effects represents a preliminary account of the general structure of relationships between aesthetic effects. As Figure 2 shows, the estimated network was interconnected with strong positive edges between the nodes *like* and *interesting* (.27), *light* and *cautious* (.24), *positive* and *interesting* (.19), *sad* and *rough* (.19), *hard* and *cold* (.18), and *positive* and *peaceful* (.17). The network has strong negative edges between the nodes *peaceful* and *rough* (-.24), *cold* and *light* (-.17), *hard* and *light* (-.15), and *positive* and *sad* (-.15).

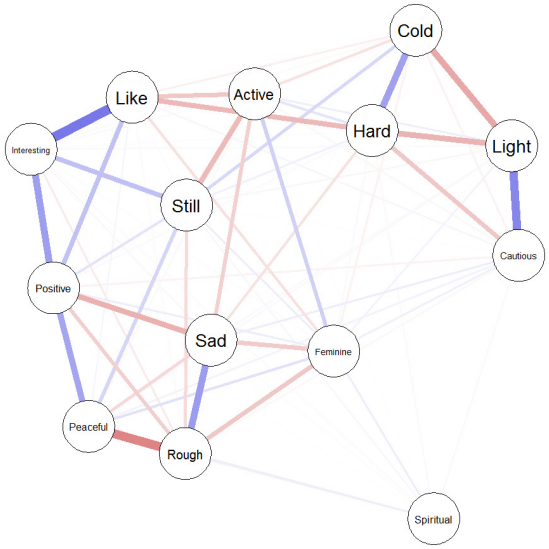

Figure 2. Global network of aesthetic effects across all artworks

Blue lines denote positive partial correlations, red lines denote negative partial correlations. All node names represent the right side of the semantic differential. That is, the item negative–positive is represented by the node "positive". A positive edge from the node active with the node positive thus means: the more active the more positive. A negative edge means the more active, the more negative. Thickness represents the strength of the association scaled to the largest partial correlation (r = .27 between "like" and "interesting").

With regard to centrality as measured by expected influence, *interesting* has the highest expected influence in the network followed by *positive*, *cautious*, and *still*. This is plotted in Figure 3. Notably, *rough* has a very low level of expected influence and *spiritual* falls somewhere in between.

An alternative approach to estimating a global network would be to average the raw data across artworks (i.e., creating a mean score for each aesthetic effect) and estimate a network from these means. To estimate the robustness of our results, we also estimated the global network this way, the corresponding figures can be found on the OSF: https://osf.io/zqxbm/. We measured the similarity of the two global networks by correlating the adjacency matrices r = .83; differences were mainly due to the second method leading to a sparser network due to regularization.[4] In addition, the correlation between the centrality of the two networks showed high similarity (r = .94). We conclude that results are reasonably robust to the different estimation methods.

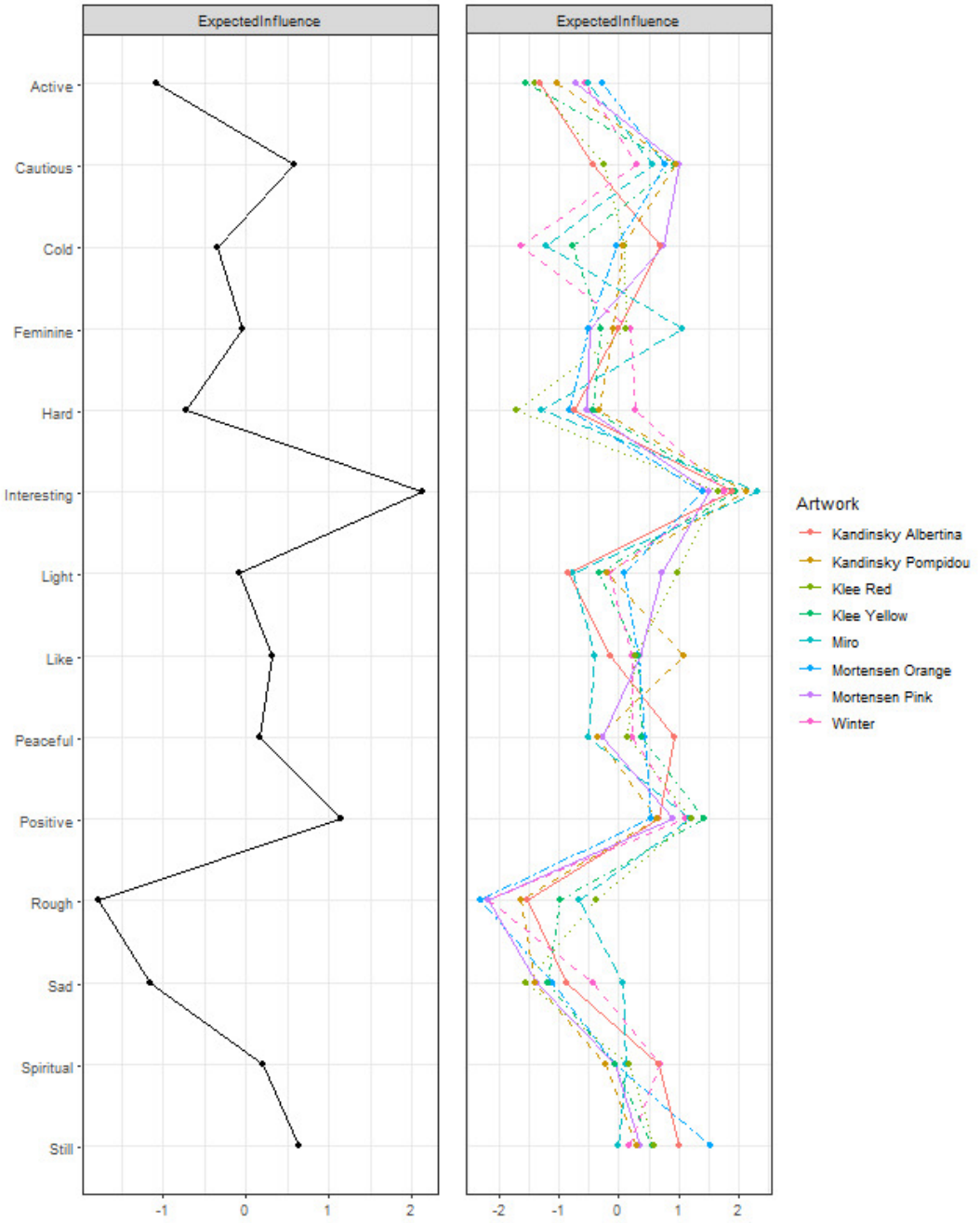

Figure 3. Standardized centrality measures of expected influence for each aesthetic effect of the global network on the left and for each individual artwork network on the right

3.2. Individual artwork networks

Since the network structure may vary depending on the artwork, we also estimated the aesthetic effects network per artwork, shown in Figure 4. The right panel of Figure 3 represents the corresponding centrality plot. Though we aimed to include homogenous artworks on the assumption that the artworks would be more comparable, we could not a priori know to what extent this assumption was valid. As such, an analysis of the individual artwork networks provides more insight in this direction as well as providing indications on how much (even small) differences between artworks impact the estimated network structure. As noted, we also assessed the accuracy and stability of the resulting

4 Suppose an edge weight is 0 in seven of the individual artwork networks and .4 in one of them. When we take an average over those edge weights, the edge weight will be above zero. In our first statistical approach, regularization comes first and then an average is taken afterwards, in the second this order is reversed, leading to a sparser network.

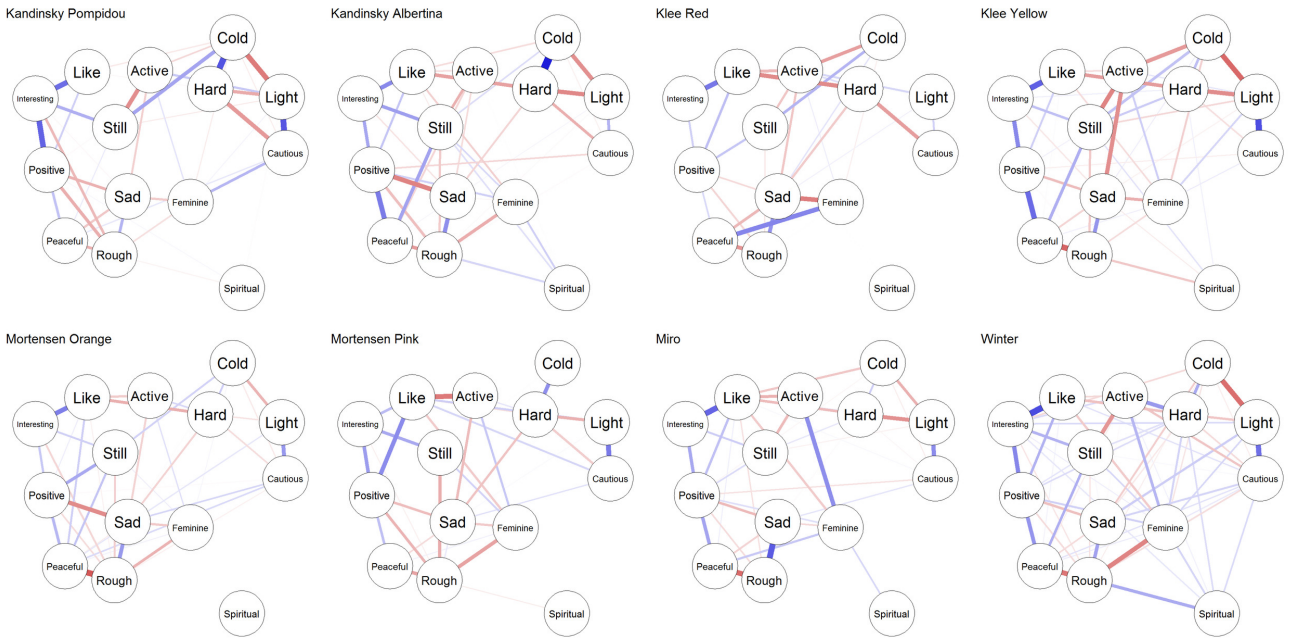

Figure 4. Aesthetic effects networks for each individual artwork

As in Figure 1, all node names represent the right side of the semantic differential. That is, the item negative–positive is represented by the node "positive". A positive edge from the node active with the node positive thus means: the more active the more positive. A negative edge means the more active, the more negative. Thickness represents the strength. All networks use the same graphical standardization (average layout, maximum edge weight = .50), which means that the strength of the edges can be compared across networks.

networks, following Epskamp et al. (2018), with 2000 samples (corresponding plots can be found in the Supplementary Material). While no clear guidelines exist, based on the prior literature, we consider the networks to be estimated with moderate stability. 95% CIs around edge weights are not small, and point estimates of edge weights hence need to be interpreted with some care. However, the edge weights difference test shows that many edge weights differ significantly from each other for the majority of artworks, indicating that the stronger edges can be meaningfully distinguished from the weaker edges.

Figure 4 shows considerable similarities across the networks. For example, the positive association between *interesting* and *like* is present in all networks, and the relation is relatively strong in a consistent way. In addition, only the Winter network (bottom row, 4th network) includes an association between *active* and *cautious,* and the relation is weak. Several differences also emerge. For instance, both artworks by Paul Klee (top row, 3rd and 4th network) have a strong negative association between *cold* and *hard*, whereas the other networks feature strong positive associations between these aesthetic effects. From the centrality plot (Figure 3, right panel), we can see that there is variability in expected influence depending on artwork. For example, *light* has a relatively high expected influence for Mortensen Pink and Klee Red compared to the other artworks. There is also some consistency across artworks, for example, *interesting* and *positive* have high expected influence for all artworks.

As a next step to investigate cross-network variability in more detail, we derived an index of network similarity by correlating adjacency matrices and centrality across artwork networks (Table 2). The three lowest correlations (between r = .51 and r = .58) of the adjacency matrices correlations are moderate, all other correlations indicate strong similarities. The centrality correlations show a similar pattern, with 5 correlations in the moderate range, and all other correlations in the strong range. To put this into perspective: The highest correlation reported by Rhemtulla et al. (2016), who compared networks of substance abuse symptoms across samples, was .64, with most other correlations in the .20-.50 range.

3.3. Variability network

As a final step, we assessed the variability of edge weights across networks. Figure 5 represents a network in which edges represent the *variability* in connection strength across the artworks rather than average connection strength. The network is scaled to a standard deviation of .15. In this network, the greatest variability is found between the associations of *cold* and *hard* (.14). Another relatively variable association is between *cold* and *light* (.12). Looking at Figure 4, we can see that these differences between the association with *cold* and *hard* may well be driven by the two artworks by Paul Klee. As noted, they include a negative association between these aesthetic effects while the other artworks include a positive association. Together these results indicate that there is some variation in the associations between the aesthetic effects dependent on artwork—however, aesthetic effects networks seem to be relatively similar in their structure.

4. Discussion

These results allowed us to formulate a preliminary account of the general structure of relationships between aes-

Table 2. Correlation matrix of artwork networks

Artwork	Kandinsky Pompidou	Kandinsky Albertina	Klee Red	Klee Yellow	Mortensen Orange	Mortensen Pink	Miro	Winter
Kandinsky Pompidou		.71	.69	.87	.81	.89	.60	.72
Kandinsky Albertina	.80		.70	.74	.76	.67	.53	.61
Klee Red	.58	.51		.76	.63	.69	.56	.46
Klee Yellow	.83	.78	.69		.76	.75	.70	.78
Mortensen Orange	.71	.76	.70	.79		.87	.46	.69
Mortensen Pink	.68	.74	.57	.68	.72		.42	.62
Miro	.72	.75	.68	.82	.79	.70		.70
Winter	.75	.80	.55	.80	.80	.71	.79	

Note: Lower triangle are adjacency matrix correlations and upper triangle are centrality correlations

thetic effects. From this general structure, hypotheses can be derived on how aesthetic effects relate to each other. For example, participants in our study who rate an artwork as *happy* are likely to also rate that artwork as *positive*, *feminine*, and *smooth* since these nodes are strongly connected. Though some of these associations may feel like common sense, recent empirical work has shown that people have a relatively low level of agreement on the aesthetic effects they attribute to artworks (Specker et al., 2020). In addition, we found that (in order) *interesting*, *positive*, *cautious*, and *still* have the highest expected influence making these nodes more likely to spread activation through the network. The expected influence of interesting and positive was stable across networks, whereas *cautious* and *still* varied more for the individual artwork networks. Hence, if the aim is to manipulate the network, one of these four nodes would be a logical candidate. Furthermore, when considering a real-life situation, the fact that *interesting* had the highest expected influence may suggest that this could be the starting point of an aesthetic experience: We may first need to find an artwork interesting to then start the associative process.

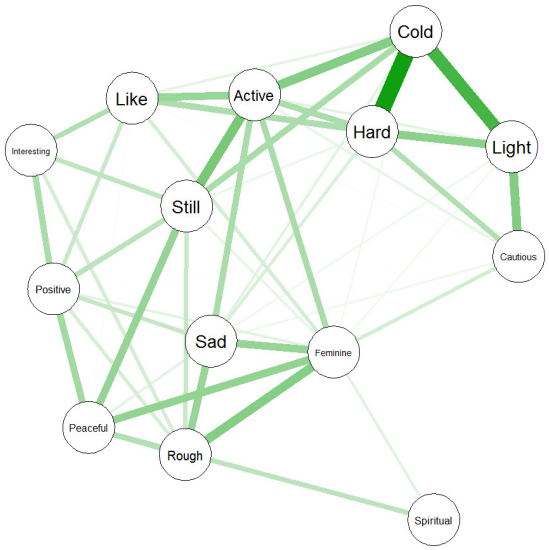

Figure 5. Variability network

Each edge represents the standard deviation across the edge weights of each individual artwork network. Thicker edges imply a higher variability of each given edge. The network is scaled to a standard deviation of .15.

5. Study 2

A limitation to Study 1 is that different theoretical models can give rise to the same correlations among items (Fried & Cramer, 2017; Kruis & Maris, 2016; Van Der Maas et al., 2006). It is not possible to figure out which model underlies the data based on estimating models, but it is possible to distinguish between the models by experimental manipulation.

If the underlying model is a network model, changing one node in the network (e.g., making an artwork appear more positive) should lead to a change in other nodes due to their interrelations. In contrast, if the underlying model is a common cause model (like the EPA), this should not happen due to the causal direction the model proposes: Evaluation, in the EPA model, is the shared causal origin for both *positive* and *peaceful*.[5] Thus, making an artwork appear more positive should not change peaceful (or another node) because the underlying cause (Evaluation) has not been changed.

This is perhaps most easily understood when drawing a parallel with illnesses such as measles. If a patient has

5 See footnote 1.

measles, this will lead to corresponding symptoms such as fever and Koplik's spots. In this situation, symptoms are passive indicators of the underlying disease, similar to the EPA model. Treating the symptoms will alleviate suffering, but it will not cure the disease: a cure has to target the disease itself, not its indicators. The same applies to our case: Changing the rating of positivity should not lead to a change in Evaluation and thus should not influence how the artwork is rated on the other indicators. Thus, a study that changes one node in the network could differentiate between a common cause and a network model. If other nodes change as a consequence of this manipulation, this would provide evidence for a network model; if they do not, this would provide evidence for a common cause model.

In order to test this, one needs a target node to manipulate. The AEN itself does not give an account of how the stimulus activates the network, it only postulates that the stimulus can activate the network. However, one can draw from the literature to generate hypotheses on how an artwork may activate the AEN. Since research shows that brightness of colors is generally associated with positivity (Lakens et al., 2012, 2013; Meier et al., 2004, 2015; Specker et al., 2018; Specker & Leder, 2018), we decided to manipulate the brightness of artworks as a means to activate the node of positivity. This manipulation is particularly suitable since there are indications that the association between brightness and positivity applies to the general brightness level of complex images (Lakens et al., 2013) as well as that it is universal (Specker et al., 2018), and *positivity* had a high expected influence in Study 1. This means that the manipulation should be applicable to artworks and be relatively insensitive to individual differences. From our AEN model, this manipulation should lead the node of positivity to be activated, and from this node the activation can spread throughout the network. This is a general hypothesis that assumes that if positivity changes, it can have an effect on the network as a whole. This would be strong evidence for the AEN model, because common cause models (like the EPA) exclude direct influences of positivity on *any* of the other nodes.

Nonetheless, based on the general network structure identified in Study 1 (Figure 2), we also formulated specific hypotheses as to which nodes were most likely to be affected by our manipulation based on the strength of their connection to positivity. Notably, this manipulation should lead to the artwork being seen as *peaceful, smooth, and happy*. These are direct effects, but we also assume indirect effects that are caused not by direct connections with positivity but are a result of a longer causal chain. Thus, we predicted that *still, peaceful, liking,* and *interest* would go up (lighter images are more still) and that *sad, rough,* and *cautious* would go down (lighter images are less sad). We pre-registered our study: https://osf.io/7upyh/register/5771ca429ad5a1020de2872e. To ensure that our manipulation would be effective, we first conducted a pilot-study to test if the brightness–positivity association would translate to artworks.

5.1. Pilot-study

We adapted the methods of Specker et al. (2018) and Specker & Leder (2018), and used an Implicit Association Test (IAT) as well as an explicit rating task that were counterbalanced. Participants saw dark and bright versions of the artworks used in Study 1. These versions were created by use of GIMP software making them either 30% darker or 30% brighter. We had 27 participants[6]—mean age = 22.93 (SD = 6.94), 18 female, none identifying as other—all students of the University of Vienna who received course credit for their participation. All participants participated voluntarily and completed the experiment in German. Results indicated a strong implicit association between brightness and positivity, $t(26) = 13.08$, $p < .001$, $d = 2.52$, 95% CI:[1.73,3.29], as well as a strong explicit association between brightness and positivity: $t(26) = 4.994$, $p < .001$, $d = .96$, 95% CI:[.49,1.41]. Given the guidelines by Cohen (1988) and also more recent suggestions (e.g., Sawilowsky, 2009), both effects can be considered as large (>.80) and the implicit effect as "huge" (>2.00), indicating that the effects should be generalizable to artworks and that our manipulation should be effective. The dataset and analysis syntax can be found on the OSF: https://osf.io/3n8zy/.[7]

5.2. Main Study

Our method for Study 2 was similar to Study 1. Participants saw eight artworks and rated each artwork on 14 scales. However, in this study, there were three versions (control, dark, and bright) of each artwork. Dark and bright versions were the same as in the pilot-study. Control versions represent "original" versions of the artworks, meaning the same version as in Study 1. Thus "control version" refers to the fact that these images were not manipulated. Since these images are all reproductions of artworks and thus not strictly "originals" we use "control version" throughout the text to refer to these images. From the association between brightness and positivity it should be the case that: bright version > control version > dark version for ratings of positivity which would constitute a manipulation check. If this holds, one can then analyze whether the manipulation had the expected effect.

To make the variation in brightness salient, we wanted to ensure that each participant saw control, dark, and bright versions of artworks. At the same time, to cancel out effects of repeated exposure, we wanted each participant to see each artwork in only one version. We created three groups which differed in which version of the artwork they saw (Table 3). These groups were not used as a basis for analysis. The experimental script, final dataset, and analysis scripts

6 Our initial sample consisted of 28 participants; one participant was excluded because she did not speak German.

7 Due to copyright, the images are not available on the OSF, though they can be seen by running the OpenSesame script from Study 2 and will, of course, be shared upon request.

Table 3. Presentation of Images

	Version		
Shorthand Title	Group 1	Group 2	Group 3
Klee Yellow	Dark	Control	Bright
Klee Red	Bright	Dark	Control
Kandinsky Albertina	Dark	Control	Bright
Kandinsky Pompidou	Bright	Dark	Control
Mortensen Pink	Bright	Dark	Control
Mortensen Orange	Dark	Control	Bright
Miro	Control	Bright	Dark
Winter	Control	Bright	Dark

are made available on the OSF: https://osf.io/3n8zy/.

5.2.1. Participants

We tested 133 participants (22 male, 111 female, none identifying as other; mean age = 20.41, SD = 2.60). We collected a sample from the same participant pool as Study 1 in order to have comparability across the two studies. All participants participated voluntarily, completed the experiment in German, and were students of the University of Vienna who received course credit for their participation.

5.2.2. Procedure

As in Study 1, participants saw 8 artworks which they rated on 14 scales. Different from Study 1, participation took place in the lab, the study was self-paced, and presentation order of the scales was randomized. Upon arrival, participants read and signed the informed consent form, and afterwards completed the rating task.

5.3. Results

To analyze our results we first did a manipulation check to assess if our manipulation was effective using a one-way ANOVA with version (bright, dark, control) as an within-subjects independent variable and positivity as a dependent variable. If our manipulation was effective it should be that the brighter an image, the more positive it is rated (so: bright version > control version > dark version). This is exactly what we found, $F(2,264) = 3.77$, $p = .024$, $\eta G^2 = .018$, representing a small effect based on Cohen (1988), illustrated in Figure 6. It has to be noted that the effect was smaller than anticipated based on the pilot-study ($d_{\text{pilot study}} = .96$). This is most likely due to the fact that in the pilot-study participants saw two versions of the same image, thus leading to a more direct comparison based on the brightness feature (making brightness more salient), whereas in this study participants only saw one version of each image.

Second, we conducted a MANOVA with version (bright, dark, control) as a within-subjects independent variable and all aesthetics effects (with the exception of positive) as dependent variables to test whether the manipulation changed how the aesthetic effects were rated. The MANOVA

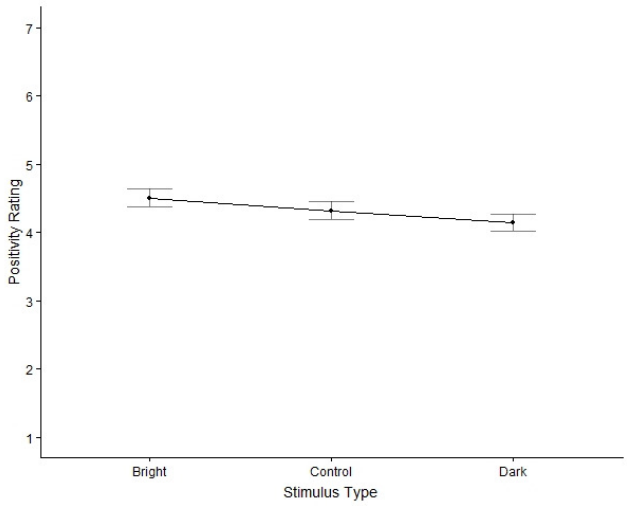

Figure 6. Mean positivity ratings between stimulus conditions

was significant, $F(2, 264) = 3.55$, $p < .001$, $\eta^2 = .154$, representing a large effect based on Cohen (1988), which we interpret as evidence for the AEN over the EPA model.

To test our specific hypotheses we ran a one-way ANOVAs with version (bright, dark, control) as an within-subjects independent variable for each dependent variable seperately. All ANOVA results and corresponding means and standard deviations are reported in Table 4. All corresponding figures can be found on the OSF: https://osf.io/3n8zy/.

As predicted, we found that darker images were significantly perceived as *sadder*, however, we did not find significant effects for *liking*, *interest*, *still*, and *peaceful*.

5.4. Discussion

One thing is clear from these results: they are not in accordance with a common cause perspective which would be unable to explain the significant MANOVA. Nonetheless, these results do bring up new questions for the AEN.

A limitation to Study 2 is that it operates on simple principles, including selective influence: the idea that one thing would only influence one other thing (rather than multi-

Table 4. Follow-up ANOVA and descriptive statistics per aesthetic effect

Aesthetic Effect	DFn	DFd	F	p	Gη²	Mean (SD)		
						Bright	Control	Dark
Aggressive–Peaceful	2	264	1.35	.26	.007	4.42 (1.07)	4.31 (1.09)	4.21 (1.09)
Intrusive–Cautious	2	264	.86	.42	.005	3.87 (1.18)	3.73 (1.06)	3.69 (1.06)
Happy–Sad	2	264	21.12	<.001	.090	3.49 (.90)	3.68 (.87)	4.17 (.96)
Dislike–Like	2	264	.54	.59	.003	3.91 (1.26)	4.02 (1.21)	4.06 (1.31)
Bodily–Spiritual	2	264	1.16	.32	.006	4.3 (1.35)	4.07 (1.24)	4.16 (1.1)
Lively–Still	2	264	2.68	.07	.013	3.69 (.99)	3.5 (.98)	3.77 (1.03)
Masculine–Feminine	2	264	8.08	<.001	.044	4.35 (.98)	4.19 (1.11)	3.83 (.98)
Passive–Active	2	264	.76	.47	.004	4.44 (.94)	4.45 (1.01)	4.32 (1.14)
Smooth–Rough	2	264	2.79	.06	.014	3.81 (1.14)	4.09 (1.12)	4.09 (1.04)
Heavy–Light	2	264	13.93	<.001	.067	4.47 (1.05)	4.15 (1.01)	3.81 (1)
Uninteresting–Interesting	2	264	.52	.60	.002	4.34 (1.16)	4.48 (1.13)	4.43 (1.26)
Warm–Cold	2	264	.01	.99	<.001	3.85 (1.19)	3.85 (1.19)	3.87 (1.17)
Soft–Hard*	2	264	.95	.50	<.001	3.8 (1.05)	3.93 (.94)	3.94 (1.11)

*In this case, the assumption of sphericity was violated, so the value in the F column represents a Greenhouse-Geisser epsilon and all other values represent corrected values.

ple other things). In our case, a change in brightness is assumed to directly influence *positivity*, and only *positivity*. This assumption can rightfully be questioned, specifically in the case of the found significant effect on *heavy–light*. It would be possible that this effect was an indirect effect of *positivity*, however, our manipulation could also have influenced the "weight" node directly, given that the literature on cross-modal correspondences shows an association between brightness and weight (Alexander & Shansky, 1976; De Camp, 1917; Walker et al., 2010; Wright, 1962).

Nonetheless, though a direct influence of brightness on more than just *positivity* brings up new questions with regard to the AEN, this seems an even more difficult phenomenon for a common cause perspective. Though it would be possible to introduce a new common cause model where brightness of the artwork directly influences all three EPA factors or solely the Evaluation factor, this model would need to be able to explain the results found for specific aesthetic effects. In this model, it seems even more puzzling why brightness would influence *happy-sad* (and *positive-negative*) but none of the other terms associated with the Evaluation factor. If there is a direct effect of brightness on Evaluation, then all related specific terms should be influenced. Similarly, the existence of an underlying causal latent factor becomes rather questionable when its indicators can be influenced independently from each other. In sum, it would be possible to create complex factor models that potentially could also explain our results; however, according to Occam's razor, in competitions of equal probability, the simpler explanation should be given priority. Note that we do not mean to imply here that network models/theory are/is sparse in and of itself, but rather that, given that any kind of network model could explain this phenomenon—whereas only a very specific complex factor model could—it is a sparse(r) explanation for this specific phenomenon.

With regard to our predictions for specific terms, the unexpected results can be explained in several ways; however, the simplest explanation may be that of Simpson's paradox: a statistical relation exists on one level (e.g., between-persons), but the opposite/no relation exists on another level (e.g., within-person). The AEN (Figure 1) is constructed on the between-person level, contrasting the within-person MANOVA. While this does not influence the main theoretical scope of the AEN—that change in one node should lead to a change in another node—it could influence the predictions based on the specific network structure of the AEN. Though Simpson's paradox can generally play a role in psychological phenomena, a difference between the between-person and within-person level seems especially plausible for aesthetic phenomena. Common sayings like "beauty is in the eye of the beholder" already hint at between-person differences in aesthetic phenomena. Furthermore, these intuitions have been substantiated empirically (e.g., Leder et al., 2016) and, specifically relevant for our study, recent work (Specker et al., 2020) has shown between-person disagreement with regard to aesthetic effects. At the same time, within-person stability has been observed, even for people with memory impairment (specifically, Alzeihmer's; Graham et al., 2013). We will discuss how individual differences can be incorporated in a network perspective in more detail in the General Discussion.

6. General Discussion

We presented a new perspective that changes the way we, at least formally, conceptualize aesthetic effects and, to a larger degree, aesthetic experience. This network perspective introduces a more process-oriented view. While most theoretical models do conceptualize aesthetic experience as a process (Leder et al., 2004; Locher et al., 2010; Pelowski et al., 2017; Tinio, 2013), they generally include a large amount of potentially relevant variables, often with a lack of clear hypotheses regarding the interrelation of the differ-

ent sub-processes and variables involved. With the AEN, we provide an explicit account of a specific cognitive process involved in aesthetic experience.

Note that, therefore, the AEN supplements previous models rather than replaces them. The aim is to substantiate existing models by providing concrete models for variables, processes, and interrelations of these models. As such, even though the current study focuses on only one cognitive process, this new approach can be applied to aesthetic experience in general. When taking this wider perspective, future work could model other variables of interest, such as relevant individual differences (e.g., art interest) or emotions.

Finally, the AEN offers a new perspective. We believe that this perspective—refocusing on understanding the processes underlying aesthetic experience—can lead to valuable insights into how people experience art. However, the AEN is very much a theory under development. Study 1 aimed to propose a preliminary structure that was consequently tested in Study 2, and results of Study 2 indicate the need to revise and update the theory further; though the general idea of an underlying network was supported, the specific network structure was not. Theory formation is a long process, and we hope this initial report provides impetus for future research. Below, we consider the limitations of the current work and possible future directions in more detail.

6.1. Limitations and Future Directions

6.1.1. Individual Differences

As noted in the introduction, the way a stimulus influences the network may vary across people; in addition, the network structure may differ across people (both are illustrated in Figure 7). These differences can potentially explain—or, at least, help us better understand—why people have different experiences when looking at the same artwork, as well as to investigate why people have similar experiences when looking at different artworks. These questions are central if we want to understand how people experience art.

Differences in general structure may occur due to differences in experience (e.g., differences in art interest or knowledge), see below. Similarly, differences in the way a stimulus influences the network may occur due to which parts of the artwork the viewer pays attention to. For example, using eye-tracking, Pihko et al. (2011) showed that art experts had different viewing strategies (as reflected by target, location, and path of fixations) leading them to pay attention to different aspects of the paintings than art novices.

Theoretically, the AEN can be connected to other theoretical models mainly proposed within research on personality—specifically the cognitive-affective personality system (CAPS; Mischel & Shoda, 1995) and other models conceptualizing personality as a dynamic system (Beck & Jackson, 2020; Cramer et al., 2012). What all these approaches share is that they propose to view personality as a dynamic system in order to understand similar questions as to interindividual (in our case, "why do different people

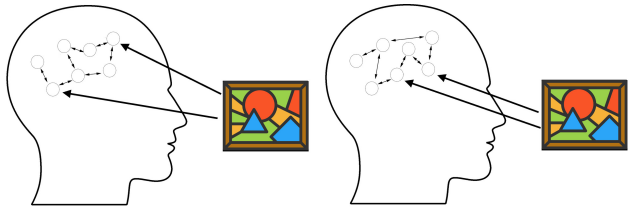

Figure 7. Conceptual model of how an artwork influences two people differently

The same painting influences the person on the left differently from the person on the right by activating different nodes in their network.

have different experiences with the same artwork?") as well as intra-individual differences ("why do people have similar experiences with different artworks?", or similarly, "why does the same person have different experiences with different artworks?"). Whereas in personality research there is an interaction between the person and the situation, in art we deal with an interaction between the person and the stimulus. Similar to the approach in personality, what this requires is to look at the person, the stimulus, and their interaction. As Mischel & Shoda (1995) stated: "The theory views the person not as reacting passively to situations nor as generating behavior impervious to their subtle features, but as active and goal-directed, constructing plans and self-generated changes, and in part creating the situations themselves" (p.252). This situation is analogous to what we have in our paper so far called the "active role of the viewer" in the AEN. To give a concrete art specific example, the Pihko et al. (2011) study cited above, indicated that people have different viewing strategies: By paying attention to different aspects of an artwork viewers can, in this way, actively influence their perception and experience of artworks.

Below, we describe some empirical approaches that can be taken in this direction (i.e., group-based comparisons, mixture-network modelling, latent class analysis). Note that for the AEN to progress as theory, it would be necessary to formulate a comprehensive theoretical approach similar to the approaches in personality psychology noted above (Beck & Jackson, 2020; Cramer et al., 2012; Mischel & Shoda, 1995).

6.1.2. Group-based Comparisons

Currently, structural differences can be investigated by looking at differences on a group level. To give some examples: art experience differs based on expertise (Chamberlain & Wagemans, 2015; Chirumbolo et al., 2014; Leder et al., 2014; Winston & Cupchick, 1992), thus one could investigate whether art experts (as a group) have a more strongly connected network than lay people (as a group). Based on findings related to art styles (Augustin & Leder, 2006; Leder et al., 2012), one could also compare a network for abstract art with one for figurative art.

Both of these approaches could provide new and interesting information that cannot be gained from methods used so far. However, both require averaging over data in order to generate a network. This is already highly relevant in

non-stimulus-bound cross-sectional data where networks are created by averaging over people. In our stimulus-bound case, this becomes even more relevant because we average not only over people, but also over stimuli.

6.1.3. Mixture Network Modeling

What in the future could be promising is mixture network modeling. Within a mixed model, averaging is not required since both the between and the within-subjects effects of independent variables are modelled at the same time (Baayen et al., 2008). Because these models model random error at all levels of analysis (Nezlek, 2001), they can account for dependencies such as responses to stimuli being dependent on individual participants (i.e., there is a person by stimulus interaction). In fact, recent studies within empirical aesthetics use linear mixed effects models specifically to account for differences in the person by stimulus interaction (Brieber et al., 2018; Gartus & Leder, 2014; Lauring et al., 2016; Leder et al., 2016; Silvia, 2013). The possibility of extending these models to networks holds great potential for understanding individual differences in aesthetic experience since these differences could be explicitly connected to differences in network structure. Unfortunately, mixture network modelling is currently not available (see Fried & Cramer, 2017, for a comprehensive outline of some of the methodological challenges in the field).

6.1.4. Latent Class Analysis

However, latent class analysis is available and does not (like the approaches above) rely on a priori defined groups. Latent class analysis can be used to derive latent classes from the data. These classes can consist of either artworks or people. Essentially, what this would entail is that, within a given subgroup, people (or artworks) share a network structure, whereas across groups the network structure differs. The possibility to test for subgroups either of people or of stimuli (and ideally both) would be extremely valuable in our stimulus-bound case since this typically includes averaging over both. Furthermore, identifying latent classes of artworks that share a network structure could be beneficial in further research investigating differences between people. Since artworks within one latent class will be similar, this makes it possible to attribute differences between the reactions to these artworks to the person (or person stimulus interaction) rather than the stimulus. Furthermore, from an interdisciplinary perspective, latent classes of artworks would allow for an art historical analysis of the features these artworks share, and could create some understanding as to properties that are inherent in the artwork or that can be attributed to the artwork. Though the results of Specker et al. (2020) are rather sobering in this direction, given that they could not find agreement between people on different properties of artworks, this perspective could offer a new line of investigation into this direction.

6.1.5. Generalizability

This would also address limitations of our study in terms of generalizability. The generalizability of our findings is limited by our homogenous set of participants and our homogenous set of stimuli. The homogeneity of our participants makes it unclear to what extent our results are generalizable to populations that do not consist of so-called "WEIRD" (Western Educated Industrialized Rich Democratic; Henrich et al., 2010) people.

The homogeneity of our stimuli makes it unclear to what extent our results are generalizable to the whole range of abstract art, as well as to the even wider range of artworks in general. Using homogeneous stimuli was beneficial to our aim of estimating a general structure of aesthetic effects that would generalize across artworks. We found evidence for this generalizability by finding low variance across artworks (Figure 5) and high correlations of edge weights between the artwork networks (Table 2). However, this network similarity may, in part, be driven by our homogenous set of stimuli and participants.

The homogeneity of our stimuli likely limits the variance between different artwork networks since the different artworks are relatively similar. The homogeneity of our sample further limits the variance between different artwork networks since all individual artwork networks were derived from the same sample. Nonetheless, if the homogeneity of our sample limited the variance in our data, this would mean that people are relatively consistent in their associations between aesthetic effects (network structure) across artworks.

A final limitation on generalizability is that in this study we worked with reproductions of artworks rather than with genuine pieces as well as that participants in Study 1 could only view the artworks for a limited amount of time (75s). Though both approaches are common practice in the field, it is unclear how these methodological aspects would influence the generalization to "real life" interactions with artworks. With regard to the use of reproductions, a recent meta-analysis (Specker et al., 2021) did not find evidence for a genuineness effect (i.e., a difference in aesthetic experience between genuine artworks and their reproductions). This could be interpreted as support for the generalizability of studies working with reproductions; however, there are several limitations to the work in this direction. Specifically, Specker et al. (2021) only found 11 studies, of which 8 had a context confound—i.e. genuine artworks seen in the museum compared to reproductions seen in a lab—making the above conclusion about generalizability not as straightforward (for a full discussion of this topic see Specker et al., 2021). In any case, future studies should consider these methodological aspects.

6.1.6. Interdisciplinary approaches

As noted in the introduction, the current paper already presents an interdisciplinary approach between art history, empirical aesthetics, and network approaches. Nonetheless, we still advocate for an even more interdisciplinary approach in the future. As already mentioned in the introduction, there is relevant work done in cognitive psychology (such as work on semantic networks). For example, we briefly mentioned the notion of spreading activation in the introduction. Within this framework, parameters can be specified such as activation decay (i.e., how long a node stays activated after activation onset) and amount of ac-

tivation in each node. These parameters could differ between people, which would present a different perspective on the individual differences discussed above, and on the results of our Study 2. An investigation into spreading activation—e.g., a simulation study using the 'spreadr' package (Siew, 2019)—would be worthwhile in the future. This is just one example, and a thorough investigation on how work from different disciplines can substantiate the current approach is needed in the future.

7. Conclusion

To conclude, we have proposed a new way to conceptualize aesthetic effects by using a network approach. In addition, we have provided evidence for this approach over alternative approaches. Conceptualizing aesthetic effects as an associative process provides an explicit account of a specific cognitive process involved in aesthetic experience. In addition, it shifts theoretical and empirical focus back to a process-based understanding of aesthetic experience. Refocusing on understanding the processes underlying aesthetic experience can lead to valuable insights into how people experience art.

Research disclosure statement

We declare that we have disclosed all of the dependent variables or measures collected and all of the conditions/groups/predictors tested for each study reported in the submitted manuscript, as well as data exclusions (subjects or observations). Furthermore, we have not conducted preliminary analyses on the data to decide whether or not to collect additional data based on the outcome of those analyses.

Competing interests

The authors have no conflict of interest (financial or otherwise) with the publication of this manuscript. Eiko Fried is an Editor at *Collabra: Psychology*. He was not involved in the peer review of the article.

Data accessibility statement

Study 1 and the Pilot-study for Study 2 were not formally pre-registered. Nonetheless, both studies have data and materials available on a permanent third-party archive (Open Science Framework). The data, analysis scripts, and materials for Study 1 can be accessed at https://osf.io/zqxbm/. The data, analysis scripts, and materials for the Pilot-study of Study 2 can be accessed at: https://osf.io/3n8zy/. Study 2 was formally pre-registered; the pre-registration can be accessed at: https://osf.io/7upyh/register/5771ca429ad5a1020de2872e. The data, analysis scripts, and materials for Study 2 can be accessed at: https://osf.io/3n8zy/.

Contributions

E. Specker developed the original study idea which was then developed in discussion with H. Leder, R. Rosenberg, and E. Fried. E. Specker & E. Fried together designed Study 1, and E. Specker collected the data. E. Specker conducted the analyses on Study 1 with help and input of E. Fried who also checked the analyses and the related interpretations. E. Specker then wrote up a corresponding paper with continuous input and help of E. Fried, that was consequently shared with H. Leder and R. Rosenberg who both provided critical revisions. In parallel, E. Specker designed Study 2, pre-registered Study 2, collected, and analysed the data. The Pilot-study was designed, collected, and analysed by E. Specker beforehand. In light of this follow-up research, all authors discussed and agreed upon combining this follow-up research into one paper. This was consequently done by E. Specker and afterwards the other authors (E. Fried, H. Leder, and R. Rosenberg) all provided critical revisions. All authors approved the final version of the manuscript for submission.

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REFERENCES

Alexander, K. R., & Shansky, M. S. (1976). Influence of hue, value, and chroma on the perceived heaviness of colors. *Perception & Psychophysics*, *19*(1), 72–74. https://doi.org/10.3758/BF03199388

Anderson, J. R. (1983). A spreading activation theory of memory. *Journal of Verbal Learning and Verbal Behavior*, *22*(3), 261–295. https://doi.org/10.1016/S0022-5371(83)90201-3

Augustin, D., & Leder, H. (2006). Art expertise: a study of concepts and conceptual spaces. *Psychology Science*, *48*(2), 135–156.

Baayen, R. H., Davidson, D. J., & Bates, D. M. (2008). Mixed-effects modeling with crossed random effects for subjects and items. *Journal of Memory and Language*, *59*(4), 390–412. https://doi.org/10.1016/j.jml.2007.12.005

Beck, E. D., & Jackson, J. J. (2020). Idiographic Traits: A Return to Allportian Approaches to Personality. *Current Directions in Psychological Science*, *29*(3), 301–308. https://doi.org/10.1177/0963721420915860

Berlyne, D. E. (1974). *Studies in the new experimental aesthetics: Steps toward an objective psychology of aesthetic appreciation.* Hemisphere.

Borgdorff, H. (2009). *Artistic research within the fields of science*. Kunsthøgskolen i Bergen. https://www.science.gu.se/digitalAssets/1322/1322679_artistic-research-within-the-fields-of-science.pdf

Borgdorff, H. (2012). *The conflict of the faculties: Perspectives on artistic research and academia*. Leiden University Press. https://openaccess.leidenuniv.nl/bitstream/handle/1887/21413/file444584.pdf?sequence=1

Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry*, *16*(1), 5–13. https://doi.org/10.1002/wps.20375

Brieber, D., Forster, M., & Leder, H. (2018). On the Mutual Relation Between Art Experience and Viewing Time. *Psychology of Aesthetics, Creativity, and the Arts*, *14*(2), 197–208. https://doi.org/10.1037/aca0000210

Bringmann, L. F., Elmer, T., Epskamp, S., Krause, R. W., Schoch, D., Wichers, M., Wigman, J. T. W., & Snippe, E. (2019). What Do Centrality Measures Measure in Psychological Networks? *Journal of Abnormal Psychology*, *128*(8), 892–903. https://doi.org/10.1037/abn0000446

Brinkmann, H., Boddy, J., Immelmann, B., Specker, E., Pelowski, M., Leder, H., & Rosenberg, R. (2018). Ferocious Colors and Peaceful Lines Describing and Measuring Aesthetic Effects. *Wiener Jahrbuch Für Kunstgeschichte*, *65*(1), 7–26.

Chamberlain, R., & Wagemans, J. (2015). Visual arts training is linked to flexible attention to local and global levels of visual stimuli. *Acta Psychologica*, *161*, 185–197. https://doi.org/10.1016/j.actpsy.2015.08.012

Chirumbolo, A., Brizi, A., Mastandrea, S., Mannetti, L., & Martens, A. (2014). 'Beauty Is No Quality in Things Themselves': Epistemic Motivation Affects Implicit Preferences for Art. *PLoS ONE*, *9*(10), e110323. https://doi.org/10.1371/journal.pone.0110323

Christensen, A., & Golino, H. (2020). *On the Equivalency of Factor and Network Loadings*. https://doi.org/10.31234/osf.io/xakez

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Erlbaum.

Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review*, *82*(6), 407–428. https://doi.org/10.1037/0033-295X.82.6.407

Cramer, A. O. J., van der Sluis, S., Noordhof, A., Wichers, M., Geschwind, N., Aggen, S. H., Kendler, K. S., & Borsboom, D. (2012). Dimensions of Normal Personality as Networks in Search of Equilibrium: You Can't Like Parties if You Don't Like People. *European Journal of Personality*, *26*(4), 414–431. https://doi.org/10.1002/per.1866

Dalege, J., Borsboom, D., van Harreveld, F., van den Berg, H., Conner, M., & van der Maas, H. L. J. (2016). Toward a Formalized Account of Attitudes: The Causal Attitude Network (CAN) Model. *Psychological Review*, *123*(1), 2–22. https://doi.org/10.1037/a0039802

De Camp, J. E. (1917). The influence of color on apparent weight. A preliminary study. *Journal of Experimental Psychology*, *2*(5), 347–370. https://doi.org/10.1037/h0075903

De Deyne, S., & Storms, G. (2008). Word associations: Network and semantic properties. *Behavior Research Methods*, *40*(1), 213–231. https://doi.org/10.3758/BRM.40.1.213

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, *50*(1), 195–212. https://doi.org/10.3758/s13428-017-0862-1

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network Visualizations of Relationships in Psychometric Data. *Journal of Statistical Software*, *48*(4), 1–18. http://www.jstatsoft.org/

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods*, *23*(4), 617–634. https://doi.org/10.1037/met0000167

Fried, E. I., & Cramer, A. O. J. (2017). Moving Forward: Challenges and Directions for Psychopathological Network Theory and Methodology. *Perspectives on Psychological Science*, *12*(6), 999–1020. https://doi.org/10.1177/1745691617705892

Fried, E. I., Eidhof, M. B., Palic, S., Costantini, G., Huisman-van Dijk, H. M., Bockting, C. L. H., Engelhard, I., Armour, C., Nielsen, A. B. S., & Karstoft, K.-I. (2018). Replicability and Generalizability of Posttraumatic Stress Disorder (PTSD) Networks: A Cross-Cultural Multisite Study of PTSD Symptoms in Four Trauma Patient Samples. *Clinical Psychological Science*, *6*(3), 335–351. https://doi.org/10.1177/2167702617745092

Gartus, A., & Leder, H. (2014). The white cube of the museum versus the gray cube of the street: The role of context in aesthetic evaluations. *Psychology of Aesthetics, Creativity, and the Arts*, *8*(3), 311–320. https://doi.org/10.1037/a0036847

Graf, L. K. M., & Landwehr, J. R. (2015). A Dual-Process Perspective on Fluency-Based Aesthetics. *Personality and Social Psychology Review*, *19*(4), 395–410. https://doi.org/10.1177/1088868315574978

Graham, D. J., Stockinger, S., & Leder, H. (2013). An Island of Stability: Art Images and Natural Scenes – but Not Natural Faces – Show Consistent Esthetic Response in Alzheimer's-Related Dementia. *Frontiers in Psychology*, *4*(MAR), 107. https://doi.org/10.3389/fpsyg.2013.00107

Hallquist, M. N., Wright, A. G. C., & Molenaar, P. C. M. (2019). Problems with Centrality Measures in Psychopathology Symptom Networks: Why Network Psychometrics Cannot Escape Psychometric Theory. *Multivariate Behavioral Research*. https://doi.org/10.1080/00273171.2019.1640103

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). The weirdest people in the world? *Behavioral and Brain Sciences*, *33*(2–3), 61–83. https://doi.org/10.1017/S0140525X0999152X

Kandinsky, W. (1947). *Point and Line to Plane*. The Solomon R. Guggenheim Foundation.

Kruis, J., & Maris, G. (2016). Three representations of the Ising model. *Scientific Reports*, *6*(1), 34175. https://doi.org/10.1038/srep34175

Lakens, D., Fockenberg, D. A., Lemmens, K. P. H., Ham, J., & Midden, C. J. H. (2013). Brightness differences influence the evaluation of affective pictures. *Cognition & Emotion*, *27*(7), 1225–1246. https://doi.org/10.1080/02699931.2013.781501

Lakens, D., Semin, G. R., & Foroni, F. (2012). But for the bad, there would not be good: Grounding valence in brightness through shared relational structures. *Journal of Experimental Psychology: General*, *141*(3), 584–594. https://doi.org/10.1037/a0026468

Lauring, J. O., Pelowski, M., Forster, M., Gondan, M., Ptito, M., & Kupers, R. (2016). Well, if they like it… Effects of social groups' ratings and price information on the appreciation of art. *Psychology of Aesthetics, Creativity, and the Arts*, *10*(3), 344–359. https://doi.org/10.1037/aca0000063

Leder, H., Belke, B., Oeberst, A., & Augustin, D. (2004). A model of aesthetic appreciation and aesthetic judgments. *British Journal of Psychology*, *95*(4), 489–508. https://doi.org/10.1348/0007126042369811

Leder, H., Gerger, G., Brieber, D., & Schwarz, N. (2014). What makes an art expert? Emotion and evaluation in art appreciation. *Cognition and Emotion*, *28*(6), 1137–1147. https://doi.org/10.1080/02699931.2013.870132

Leder, H., Gerger, G., Dressler, S. G., & Schabmann, A. (2012). How art is appreciated. *Psychology of Aesthetics, Creativity, and the Arts*, *6*(1), 2–10. https://doi.org/10.1037/a0026396

Leder, H., Goller, J., Rigotti, T., & Forster, M. (2016). Private and Shared Taste in Art and Face Appreciation. *Frontiers in Human Neuroscience*, *10*, 155. https://doi.org/10.3389/fnhum.2016.00155

Locher, P., Overbeeke, K., & Wensveen, S. (2010). Aesthetic Interaction: A Framework. *Design Issues*, *26*(2), 70–79. https://doi.org/10.1162/DESI_a_00017

Macke, F. (1964). *August Macke, Franz Marc; Briefwechsel*. M. DuMont Schauberg.

Meier, B. P., Fetterman, A. K., & Robinson, M. D. (2015). Black and White as Valence Cues. *Social Psychology*, *46*(3), 174–178. https://doi.org/10.1027/1864-9335/a000236

Meier, B. P., Robinson, M. D., & Clore, G. L. (2004). Why Good Guys Wear White: Automatic Inferences About Stimulus Valence Based on Brightness. *Psychological Science*, *15*(2), 82–87. https://doi.org/10.1111/j.0963-7214.2004.01502002.x

Mischel, W., & Shoda, Y. (1995). A Cognitive-Affective System Theory of Personality: Reconceptualizing Situations, Dispositions, Dynamics, and Invariance in Personality Structure. *Psychological Review*, *102*(2), 246–268. https://doi.org/10.1037/0033-295X.102.2.246

Nelson, D. L., McKinney, V. M., Gee, N. R., & Janczura, G. A. (1998). Interpreting the influence of implicitly activated memories on recall and recognition. *Psychological Review*, *105*(2), 299–324. http://www.ncbi.nlm.nih.gov/pubmed/9577240

Nezlek, J. B. (2001). Multilevel Random Coefficient Analyses of Event- and Interval-Contingent Data in Social and Personality Psychology Research. *Personality and Social Psychology Bulletin*, *27*(7), 771–785. https://doi.org/10.1177/0146167201277001

Ortlieb, S. A., Kügel, W. A., & Carbon, C.-C. (2020). Fechner (1866): The Aesthetic Association Principle—A Commented Translation. *I-Perception*, *11*(3), 204166952092030. https://doi.org/10.1177/2041669520920309

Osgood, C. E., Suci, G. J., & Tannenbaum, P. H. (1957). *The Measurement of Meaning*. University of Illinois Press.

Pelowski, M., Markey, P. S., Forster, M., Gerger, G., & Leder, H. (2017). Move me, astonish me… delight my eyes and brain: The Vienna Integrated Model of top-down and bottom-up processes in Art Perception (VIMAP) and corresponding affective, evaluative, and neurophysiological correlates. *Physics of Life Reviews*, *21*, 80–125. https://doi.org/10.1016/J.PLREV.2017.02.003

Pihko, E., Virtanen, A., Saarinen, V.-M., Pannasch, S., Hirvenkari, L., Tossavainen, T., Haapala, A., & Hari, R. (2011). Experiencing Art: The Influence of Expertise and Painting Abstraction Level. *Frontiers in Human Neuroscience*, *5*, 94. https://doi.org/10.3389/fnhum.2011.00094

Rhemtulla, M., Fried, E. I., Aggen, S. H., Tuerlinckx, F., Kendler, K. S., & Borsboom, D. (2016). Network analysis of substance abuse and dependence symptoms. *Drug and Alcohol Dependence*, *161*, 230–237. https://doi.org/10.1016/j.drugalcdep.2016.02.005

Sawilowsky, S. S. (2009). New Effect Size Rules of Thumb. *Journal of Modern Applied Statistical Methods*, *8*(2), 597–599. https://doi.org/10.22237/jmasm/1257035100

Schnackertz, H. J. (2010). Wirkung/Rezeption. In K. Barck, M. Fontius, F. Wolfzettel, & B. Steinwachs (Eds.), *Ästhetische Grundbegriffe*. Metzler.

Siew, C. S. Q. (2019). spreadr: An R package to simulate spreading activation in a network. *Behavior Research Methods*, *51*(2), 910–929. https://doi.org/10.3758/s13428-018-1186-5

Silvia, P. J. (2013). Interested Experts, Confused Novices: Art Expertise and the Knowledge Emotions. *Empirical Studies of the Arts*, *31*(1), 107–115. https://doi.org/10.2190/EM.31.1.f

Specker, E., Fekete, A., Trupp, M. D., & Leder, H. (2021). Is a "real" painting better than a reproduction? A meta-analysis of the genuineness effect. *Psychology of Aesthetics, Creativity, and the Arts*. https://doi.org/10.1037/aca0000399

Specker, E., Forster, M., Brinkmann, H., Boddy, J., Immelmann, B., Goller, J., Pelowski, M., Rosenberg, R., & Leder, H. (2020). Warm, lively, rough? Assessing agreement on aesthetic effects of artworks. *PLOS ONE*, *15*(5), e0232083. https://doi.org/10.1371/journal.pone.0232083

Specker, E., & Leder, H. (2018). Looking on the Bright Side: Replicating the Association between Brightness and Positivity. *Collabra: Psychology*, *4*(1), 34. https://doi.org/10.1525/collabra.168

Specker, E., Leder, H., Rosenberg, R., Hegelmaier, L. M., Brinkmann, H., Mikuni, J., & Kawabata, H. (2018). The universal and automatic association between brightness and positivity. *Acta Psychologica*, *186*. https://doi.org/10.1016/j.actpsy.2018.04.007

Steyvers, M., & Tenenbaum, J. B. (2005). *The Large-Scale Structure of Semantic Networks: Statistical Analyses and a Model of Semantic Growth*. https://doi.org/10.1207/s15516709cog2901_3

Takahashi, S. (1995). Aesthetic properties of pictorial perception. *Psychological Review*, *102*(4), 671–683. https://doi.org/10.1037//0033-295X.102.4.671

Tinio, P. P. L. (2013). From artistic creation to aesthetic reception: The mirror model of art. *Psychology of Aesthetics, Creativity, and the Arts*, *7*(3), 265–275. https://doi.org/10.1037/a0030872

Travers, J., & Milgram, S. (1969). An Experimental Study of the Small World Problem. *Sociometry*, *32*(4), 425–443. http://www.jstor.org/stable/2786545

Van Der Maas, H. L. J., Dolan, C. V., Grasman, R. P. P. P., Wicherts, J. M., Huizenga, H. M., & Raijmakers, M. E. J. (2006). A dynamical model of general intelligence: The positive manifold of intelligence by mutualism. *Psychological Review*, *113*(4), 842–861. https://doi.org/10.1037/0033-295X.113.4.842

Walker, P., Francis, B. J., & Walker, L. (2010). The Brightness-Weight Illusion. *Experimental Psychology*, *57*(6), 462–469. https://doi.org/10.1027/1618-3169/a000057

Winston, A. S., & Cupchick, G. C. (1992). The Evaluation of High Art and Popular Art By Naive and Experienced Viewers. *Visual Arts Research*, *18*(1), 1–14.

Wright, B. (1962). The Influence of Hue, Lightness, and Saturation on Apparent Warmth and Weight. *The American Journal of Psychology*, *75*(2), 232. https://doi.org/10.2307/1419606

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