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ARTICLE

What kind of impacts can artwork have on viewers? Establishing a taxonomy for aesthetic impacts

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Abstract
What kinds of impacts can visual art have on a viewer? To identify potential art impacts, we recruited five aesthetics experts from different academic disciplines: art history, neuroscience, philosophy, psychology and theology. Together, the group curated a set of terms that corresponded to descriptive features (124 terms) and cognitive-affective impacts (69 terms) of artworks. Using these terms as prompts, participants (n = 899) were given one minute to generate words for each term related to how an artwork looked (descriptive features) or made them think or feel (cognitive-affective impacts). Using network psychometric approaches, we identified terms that were semantically similar based on participants' responses and applied hierarchical exploratory graph analysis to map the relationships between the terms. Our analyses identified 17 descriptive dimensions, which could be further reduced to 5, and 11 impact dimensions, which could be further reduced to 4. The resulting taxonomy demonstrated overlap between the descriptive and impact networks as well as consistency with empirical evidence. This taxonomy could serve as the foundation to empirically evaluate art's impacts on viewers.

KEYWORDS
aesthetic cognitivism, affect, cognition, semantic network

BACKGROUND

Art affects how we think and feel. Some researchers argue that art can promote new knowledge (Baumberger, 2013; Goodman, 1968) and evoke emotional experiences that are distinct from other experiences (Menninghaus et al., 2019). Others contend that art provides knowledge and emotional experiences that are no different than other experiences (e.g. everyday emotions; Skov & Nadal, 2020; Stolnitz, 1992). Regardless of position, researchers agree that art can have an impact on our lives.

The debates over the types of impacts art can have highlights an important question: What is art good for? Art may be hedonic, a pleasurable sensory experience, it may be expressive of emotions, it may be a force for social cohesions, it may be transformative. We contend that art's value can be examined by the impacts that it produces. Identifying the impacts of art can facilitate the development of a common way to measure this aspect of art's function. For example, if art provides the viewer with new knowledge, then how does it do so? What knowledge is gained? Who is most likely to gain new knowledge? Under what circumstances? The present research aims to establish such a foundation by focusing on language—words we use to describe art and its impacts.

Language and aesthetic experience

Empirical research on aesthetics emphasizes evaluative appraisals. The most common questions posed to participants are whether they like an artwork, find it interesting, or find it beautiful. Other queries used less commonly such as how an artwork made us think or feel could provide an opportunity to understand art's various impacts (Christensen, Cardillo, & Chatterjee, 2022; Wassiliwizky & Menninghaus, 2021). Feeling curious implies a desire to know more about an artist or artwork (Silvia, 2010; Vogl et al., 2020). Having an insight or ‘aha’ moment suggests new understanding was gained in the process (Muth et al., 2015; Pelowski, 2015). Experiencing profound emotions such as sublime signals a transformation of previous ways of thinking (Pelowski et al., 2020). Collectively, these appraisals offer an opportunity to gain a better understanding of how art affects us beyond stating whether we like the art.

These appraisals refer to only a subset of possible experiences that a person might have when engaging with art (Schindler et al., 2017). Because appraisals allow us to infer people's experiences with artworks, they provide a foundation on which to design experimental studies. Curiosity and interest, for example, can differ in meaning despite both suggesting a desire to seek information. Curiosity (as defined operationally in the education literature) refers to a short-term and specific desire to seek information whereas interest refers to ongoing and sustained desire to continue to learn about something (Hidi & Renninger, 2020; Renninger & Hidi, 2020).

Exploring the semantic space of appraisals can provide a granular understanding of their meaning and associations. Sublime, for example, was defined differently by prominent philosophers Kant (1790/1986) and Burke (1759/1958). They agreed that sublime refers to awe, splendour and existential safety while also feeling afraid. They differed in whether sublime has a cognitive component: Kant suggested sublime expanded or challenged concepts and promoted insight, while Burke suggested sublime was mainly an affective experience without involvement of cognition. While experts can debate the phenomenological experience of sublime, another approach is to examine how people use the word.

Pelowski et al. (2021) asked people if they ever had a sublime experience and if so, what were its qualities. Most people reported a role for the environment (65.0%), that they felt at ease (84.2%) and that the experience had either cognitive (42.5%) or affective (35.0%) components. The authors then had people rate different emotions of their experience and applied a network science method to map the semantic space of these emotions. Such methods rely on people's verbal associations as we use in this study and will describe in detail later. The participants' responses organized along six dimensions: pleasure/beauty, transformation/insight, discrepancy/tension, negative emotion, self-awareness and arousal. Based on the core terms of these dimensions, the largest class of sublime experiences was characterized by high pleasure/beauty, high transformation/insight, high discrepancy/tension, low negative emotion, high self-awareness and moderate arousal. Their results provide support for sublime including a cognitive component and demonstrate how mapping the semantic space of appraisals can provide insight into their meaning as conceived by large groups of people.

How people appraise artworks may be affected by the visual properties of the artworks themselves. Brightness, for example, is often experienced positively (Specker, Leder, Rosenberg, et al., 2018; Specker, Leder, & Zwaan, 2018), while judgements of warmth may vary by the person (Specker, Forster, Brinkmann, Boddy, Immelmann, et al., 2020). Abstract artworks may be more challenging than representational artworks, with some people enjoying the challenge and others feeling disengaged by it (Leder et al., 2004; Pelowski et al., 2017). Formal-perceptual properties such as brush stroke and colour saturation may affect viewer's perceptual appraisals whereas conceptual-representational properties such as abstraction and symbolism may affect viewer's cognitive-affective appraisals (Chatterjee et al., 2010).

Semantic network methods have been useful in assessing the contribution of visual properties of artworks to their perceived similarity and value. Hayn-Leichsenring and colleagues compared statistical image properties of artworks to verbal descriptions of the same artworks. In one study, they found subjective ratings (e.g. structure, subjective complexity, interest, emotion) were linked to an artwork's image statistical properties (e.g. fractality, complexity, colour; Lyssenko et al., 2016). In another study, they used these same verbal descriptions and statistical image properties of abstract artworks and applied network science methods to understand the relationships between artworks and people's preferences (Hayn-Leichsenring et al., 2020). The network derived from verbal descriptions more closely related to people's preferences than the network of statistical image properties. Verbal descriptions also classified the styles of the artworks better than formal image statistics. These studies demonstrate that people's descriptions of artworks are associated with their preferences for artworks and how language and network methods can be leveraged to illuminate subjective experiences with art.

We propose that language, which provides a basis to describe artworks, also offers a window into how they make us think and feel. However, experts and the general population might not use language similarly to describe artworks or their impacts. Experts know more about different artists, styles and techniques, which may influence the language they use to describe artworks (Cotter et al., 2021; Specker, Forster, Brinkmann, Boddy, Pelowski, et al., 2020). People with more art knowledge have more nuanced emotions in response to art, which may be related to the language they use to appraise artworks (Fayn et al., 2018). Establishing a common vocabulary that can be used by experts and laypeople alike would be a useful step towards studying the impact of engaging with art, with the assumption that emotionally impactful engagements likely index the acquisition of new knowledge and understanding. Such a vocabulary could be used to identify artworks that vary on specific impacts, laying the foundation to investigate how and when these impacts occur (Christensen, Cardillo, & Chatterjee, 2022).

Present research

We aimed to establish a taxonomy to describe artworks and identify their varied impacts on viewers. To capture a comprehensive range of such terms, we recruited an expert panel of five scholars, one each from art history, neuroscience, philosophy, psychology and theology. Our panel generated a list of terms that describe visual artworks and their potential cognitive and affective impacts. Using these terms, we recruited a diverse sample of non-expert participants to generate associations with each term to better understand how a general population conceptualizes and organizes these terms. To develop a common vocabulary, we leveraged network science methods to map the space of the expert-derived terms using the participant-derived associations. First, we sought to evaluate the overlap in meaning between terms generated by the panel based on our participant's responses. After, we identified dimensions organizing the terms using hierarchical exploratory graph analysis, a network psychometrics approach to identify dimensions in multivariate data. This step allowed us to establish themes related to aesthetic cognitivism at finer and coarser levels of granularity (Christensen et al., 2021; Golino et al., 2020; Golino & Epskamp, 2017; Jiménez et al., 2022).

METHODS

Participants

One thousand people were recruited over Amazon's Mechanical Turk (MTurk). Two people were removed because their MTurk IDs could not be matched in the Qualtrics data. Ninety-nine people were removed after obvious bot and copy and paste responses were identified in a free association task (e.g. sentences or paragraphs defining the cue word). A final sample of 899 people were used in the analysis. This sample had a broad age range (M = 39.12, SD = 11.20, range = 19–77), more men (54.3% male, 44.7% female) and slightly more white/European American (75.3%) than national demographics (14.0% black/African American, 6.1% Asian/Asian American, 5.5% Hispanic/Latinx/Spanish Descent).

Materials

Development of aesthetic cognitivism terms

A panel of five aesthetics experts from different disciplines participated in two meetings to produce terms related to aesthetic cognitivism. The experts' disciplines included art history (Matthew Milliner), neuroscience (Anjan Chatterjee), philosophy (Noël Carroll), psychology (Ellen Winner) and theology (Natalie Carnes). Drawing on their expertise and experiences, they independently generated terms related to aesthetic experiences in two broad categories: descriptors (how an artwork looks) and impacts (how an artwork makes the viewer think or feel). Within these categories, sub-categories were supplied to encourage further granularity. Descriptors were labelled as formal/literal descriptors (aesthetic properties), content (depictions), expressive/tone (emotions portrayed) and evaluative (judgements), while impacts were cognitive (makes the viewer think) and affective (makes the viewer feel). In total, 269 terms were generated by the panel (182 descriptive and 87 impact).

After generating these terms, the panel met to explain, discuss and further refine their choices. The authors examined the penultimate list to clarify terms, remove duplicate and synonym terms and develop a final list. The goal of this process was to obtain a set of descriptive and impact terms that represented the breadth of the terms generated while also reducing the number of terms to be manageable for a semantic-free association task. The final list contained 193 terms comprised of 124 descriptive and 69 impact terms (see our OSF page for the original and final set of terms).

Semantic-free association task

The 124 descriptive and 69 impact terms were used as cue words in a semantic-free association task (Kenett et al., 2011). Participants were provided with a cue word, which was one of the terms derived and were asked to generate associated words in one minute. Participants were instructed to 'not use full sentences' and instead to use 'one to two words only' for their associations. They were also instructed to 'provide words that relate to the target word in the context of viewing art'. If participants did not know a cue word, then they could select 'do not know'.

Because of the large number of terms, participants were provided either descriptive or impact terms. Because of time and attention constraints, descriptive and impact terms were divided into smaller sets (four different sets of 31 for descriptive and one set of 34 and another set of 35 for impact). Participants completed one set from either descriptive or impact terms only. Participants were provided specific instructions about the terms—they were either told that they would be presented with 'descriptions of artworks' or 'emotional or cognitive impacts that artworks might have on a viewer' for the descriptive and impact sets, respectively. When presented with a cue word, the participants were prompted with the phrase 'The artwork was… [descriptive term]' or 'The artwork felt… [impact term]'. Participants were given a three minute break about halfway through the set of cue words.

Art experiences questionnaire

Participants completed an art experiences questionnaire (Chatterjee et al., 2010) that asked them eight questions about the number of formal art courses they have taken, how often they visit art museums, galleries or exhibitions, how often they read about art, and how often they make art. Participants responded using '0' to '6 or more' for questions related to number of courses and 'Almost never' to 'Every week' for questions related to how often they did something. The sum total of these responses ranged from 0 to 46 with a median of 7, mean of 13.01 and standard deviation of 12.70. The distribution was bimodal (peaks around 0–2 and 34–36) and positively skewed suggesting our sample was a mix of two groups: mostly art naïve and some art experienced (Chatterjee et al., 2010). This distribution and skew of art experience is typical of general populations studied in the empirical aesthetics literature. Given this finding, we expect our results to generalize to the broader population (rather than a more art specialized population such as our art experts, for instance).

Procedure

Participants were recruited over MTurk via a Qualtrics link. Participants provided their MTurk ID and consent before starting the study. They then received instructions about the free association task and completed an example. Next, they completed the free association task, which lasted around 25–35 min. Afterwards, the art experience questionnaire was completed followed by a demographics questionnaire. Participants responded to a quality check question 'Do you think the answers you have given here are honest and good quality that we should include them in our final analysis'? Participants were informed that they would be compensated regardless of their response to this question. Finally, participants were provided a code to submit to MTurk for compensation. Participants were compensated $6 for 45 min of their time ($8/h). All materials and procedure for our study are available on our OSF page. This study was approved by our university's Institutional Review Board.

Statistical analyses

Preprocessing free association responses

Before analysing the free association data, participants' responses were preprocessed following Christensen and Kenett's (2021) semantic network analysis pipeline. The preprocessing stage of the pipeline ensures that responses are spelled correctly, duplicate responses to the same cue are removed, and responses are stemmed (e.g. watching → watch, watched → watch, watches → watch). After the data were cleaned, responses were condensed into a response matrix where the columns are the descriptive and impact terms, and the rows are the responses participants provided. The elements of the response matrix corresponded to the number of participants who provide the response for each term. Finally, separate response matrices were created for descriptive and impact terms. This preprocessing was carried out using the *SemNetDictionaries* (version 0.2.0) and *SemNetCleaner* (version 1.3.5; Christensen & Kenett, 2021) packages in R (version 4.2.0; R Core Team, 2022).

Unique variable analysis

Although experts might use these terms in distinct ways, our objective was to derive a vocabulary that would be used by non-experts. Terms that do not differ in their meaning for laypeople are not useful for measuring the impact of an artwork. For example, if a general population does not discriminate between 'sad' and 'morose', then retaining both those terms, even if distinguishable by experts, would not be necessary or useful for our assessments.

To combine terms with similar semantic meaning based on the responses provided by participants, we performed Unique Variable Analysis (UVA; Christensen, Garrido, & Golino, 2022). UVA is a network psychometrics approach used to detect local dependence between variables (e.g. semantic similarity; Leising et al., 2020). Simulation results demonstrate that UVA performs as well as techniques such as standardized expected parameter change in exploratory structural equation modelling

(Asparouhov & Muthén, 2009) but without needing knowledge of the data's internal structure (i.e. without knowing how many dimensions underlie the data).

The approach works by applying a network estimation method and computing a network measure called weighted topological overlap (Zhang & Horvath, 2005). Weighted topological overlap quantifies the similarity between nodes in a network, which in our case represent the descriptive or impact terms. The similarity between nodes is captured by considering the strength of the edge (i.e. correlation) that connects them as well as the edges they share.

We applied the graphical least absolute shrinkage and selection operator (GLASSO; Friedman et al., 2008) network estimation method with Spearman's rho correlations (Epskamp & Fried, 2018). After, we used a threshold of 0.15 to identify terms that were roughly redundant with one another. We followed the automated approach that iteratively combines redundant terms and then repeats this procedure until no redundant terms remain (Christensen, Garrido, & Golino, 2022).

Exploratory graph analysis

To determine how the terms could be reduced to thematic groupings, we applied exploratory graph analysis (EGA). EGA is a recently developed method to estimate the number of dimensions in multivariate data using undirected network models (Golino et al., 2020; Golino & Epskamp, 2017). EGA first applies a network estimation method followed by a community detection algorithm for weighted networks (Fortunato, 2010). EGA is demonstrated to be as accurate or more accurate than more traditional factor analytic methods such as parallel analysis (Christensen et al., 2021; Golino et al., 2020).

Network estimation method

We applied the Triangulated Maximally Filtered Graph (TMFG; Massara et al., 2017) to estimate the network, which has demonstrated better accuracy than the more common GLASSO approach in count data (Golino et al., 2021). The TMFG applies a structural constraint on the zero-order correlation matrix. In this study, we used Spearman's rho correlations to estimate the zero-order correlation matrix for both the descriptive and impact terms. The structural constraint restrains the network to retain a certain number of edges ($3n$–6, where n is the number of nodes). The final network is comprised of three- and four-node cliques (i.e. sets of connected nodes; a triangle and tetrahedron, respectively).

Network estimation starts with a tetrahedron that is comprised of the four nodes that have the high sum of correlations that are greater than the average correlation in the correlation matrix. Next, the algorithm identifies the node that is not connected in the network and maximizes its sum of correlations to three nodes already in the network. This node is then connected to those three nodes. This process continues iteratively until every node is connected in the network. One property of these networks is that they form a 'nested hierarchy' such that its constituent elements (three-node cliques) form sub-networks in the overall network (Song et al., 2012).

Community detection algorithm

We applied the Louvain algorithm (also referred to as Multi-level; Blondel et al., 2008) to identify communities or dimensions of terms in the network (Golino & Epskamp, 2017). The algorithm begins by randomly sorting nodes into communities with their neighbours and then uses modularity (Newman, 2006) to iteratively optimize its community partitions by exchanging nodes between communities and evaluating the change in modularity until it no longer improves. Then, the algorithm collapses the communities into latent nodes (i.e. summing their edge weights) and starts this process over until all nodes merge into one dimension. Each pass through this process represents a level, providing a multi-level structure. The Louvain algorithm was implemented using the *igraph* package (version 1.3.1; Csardi & Nepusz, 2006) in R.

Consensus clustering

One limitation of many community detection algorithms, including Louvain, is that they are stochastic, meaning results may differ based on how variables are ordered when input (Fortunato, 2010). To overcome this limitation, we applied an approach called consensus clustering, which applies a community detection algorithm (e.g. Louvain) many times (e.g. 1000) to obtain a large number of possible results (Lancichinetti & Fortunato, 2012). Across these iterations, the proportion of times each node pairing appears in the same community is computed, resulting in a symmetric matrix. This matrix is then thresholded to eliminate small proportions of node pairings that might have occurred by chance. Following Lancichinetti and Fortunato's (2012) recommendation for the Louvain algorithm, we used a threshold of 0.30. This process repeats using the thresholded matrix until all proportions of node pairings converge to 1. The resulting matrix is block diagonal, reflecting the final communities.

Hierarchical structure

To identify a hierarchy of terms, we used an alternative aggregation approach to create 'latent' nodes in the Louvain algorithm's multi-level process. This approach starts by estimating a network (using the TMFG method) and performing the first pass of the Louvain with consensus clustering to obtain the lower order structure. Next, rather than summing the edges of the nodes in their respective communities (to obtain 'latent' nodes, as is the default in the Louvain algorithm), we estimated network scores based on the network structure and the response frequencies in the data (Golino et al., 2021). These network scores were then used to estimate EGA with Louvain and consensus clustering approach described above. The result of this second EGA reflects the higher order structure of the network (Jiménez et al., 2022).

Data and R scripts

All data and R scripts used to preprocess and analyse the data are available on our OSF page. The UVA and hierarchical EGA approaches were implemented using the *EGAnet* package (version 1.1.1; Golino & Christensen, 2022) in R. The network plots were visualized using the *ggplot2* (version 3.3.6; Wickham, 2016) and *GGally* (version 2.1.2; Schloerke et al., 2021) packages in R.

RESULTS

Term descriptive statistics

From the descriptive terms, 7710 different responses were generated. The ten most common responses were bright, happy, colourful, dull, simple, sad, bold, calm, interesting and beautiful. From the impact terms, 4888 different responses were generated. The ten most common responses were happy, angry, upset, thoughtful, inspired, joy, interested, scared, caring and mad. Between the descriptive and impact terms, 2997 responses were the same, suggesting that a large proportion of how people felt and think about artworks are reflected in how they describe them (Pelowski et al., 2020).

The total number of responses for descriptive terms were relatively normal (skew = −0.16 and kurtosis = 0.1) with a mean of 673.66, standard deviation of 113.05 and range of 351–959. Similarly, the total number of responses for the impact terms were relatively normal (skew = −0.32 and kurtosis = −0.22) with a mean of 636.74, standard deviation of 96.18 and range of 409–827.

Unique variable analysis

Based on people's free responses to the descriptive terms, 10 terms were sufficiently semantically similar to be considered redundant. These sets of terms were muted/subdued/quiet, friendly/warm, sad/melancholic, cheerful/joyful, landscape/nature, ironic/satirical, religious/spiritual, peaceful/calm, unimaginative/boring and amateur/mediocre. Based on people's free responses to the impact terms, 8 terms were semantically similar enough to be considered redundant. These sets of terms were expansive/broadening, angry/enraged, contemplative/thoughtful, despair/sad, happy/joy, frightened/horrified, revolted/disgusted and compassionate/empathetic. For both descriptive and impact terms, the frequency of these responses was summed and labels combined. There were 113 descriptive and 61 impact terms used in the EGA estimations.

Granularity of descriptive terms

The hierarchical EGA identified 17 lower order and 5 higher order dimensions of descriptive terms, which can be understood as finer and coarser levels, respectively, of semantic granularity (Figures 1 and 2, respectively).

For the lower order (fine-grain) dimensions, we report the three terms with the highest network loadings within their dimension and label them by their highest network loading (separated by semi-colons with dimension label in italics; Christensen & Golino, 2021): *ambiguous*, abstract, cryptic; *balanced*, coherent, organized; *beautiful*, impressive, amazing; *colourful*, exuberant, cheerful/joyful; *concrete*, precise, realistic; *controversial*, violence, jarring; *friendly/warm*, relatable, tender; *innovative*, original; *inspirational*, inspired, religious/spiritual; *interesting*, mesmerizing, arresting; *metaphorical*, representational, allegorical; *profound*, emotional, serious; *provocative*, probing, challenging; *sad/melancholic*, dark, suffering; *skilled*, accomplished, intricate; *still life*, portrait; *unimaginative/boring*, banal, mundane (Figure 1).

The higher order (coarse-grain) dimensions summarize the relations between the lower order dimensions and allow them to be categorized with greater abstraction (Figure 2). The first higher order

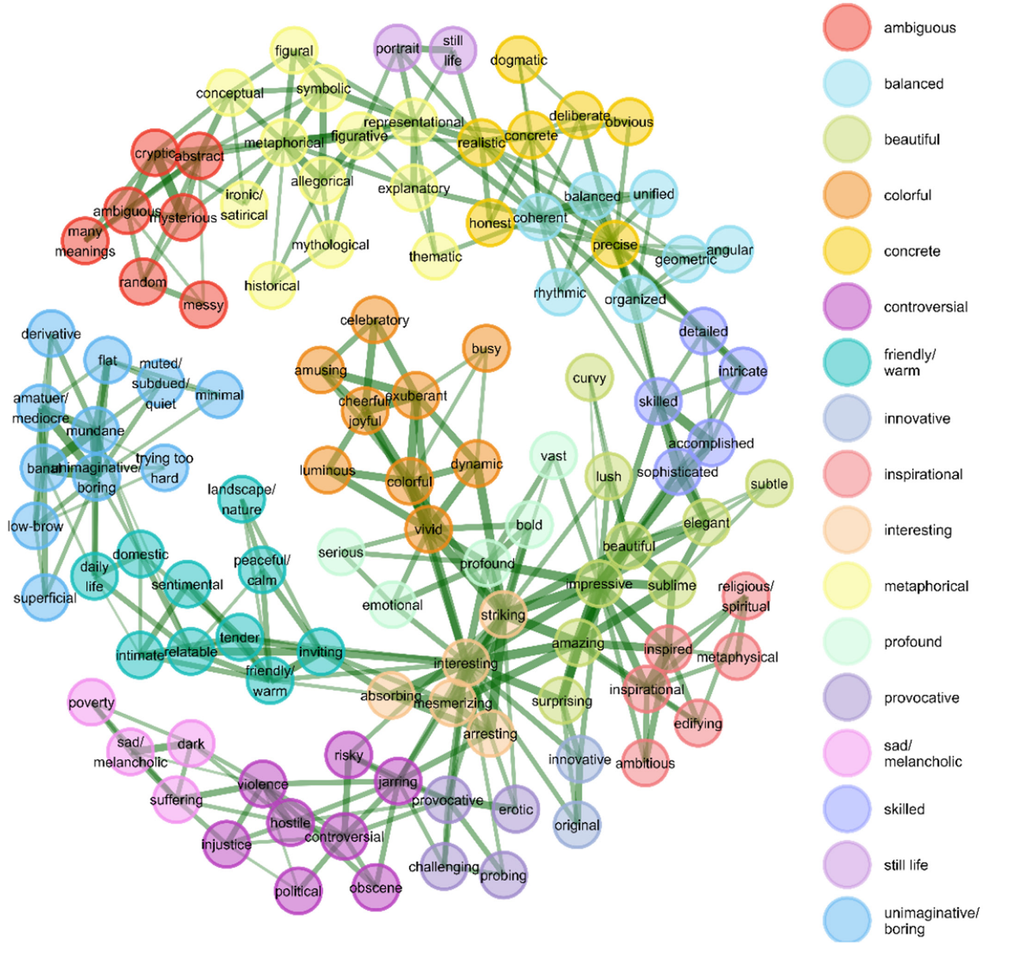

FIGURE 1 Lower order (fine-grain) dimensions of the descriptive terms. Node colour denotes lower order dimension, edge colour denotes positive (green) and negative (red) correlations, and edge size denotes size of correlation. Proximity of nodes depicts relative their relative position and semantic similarity.

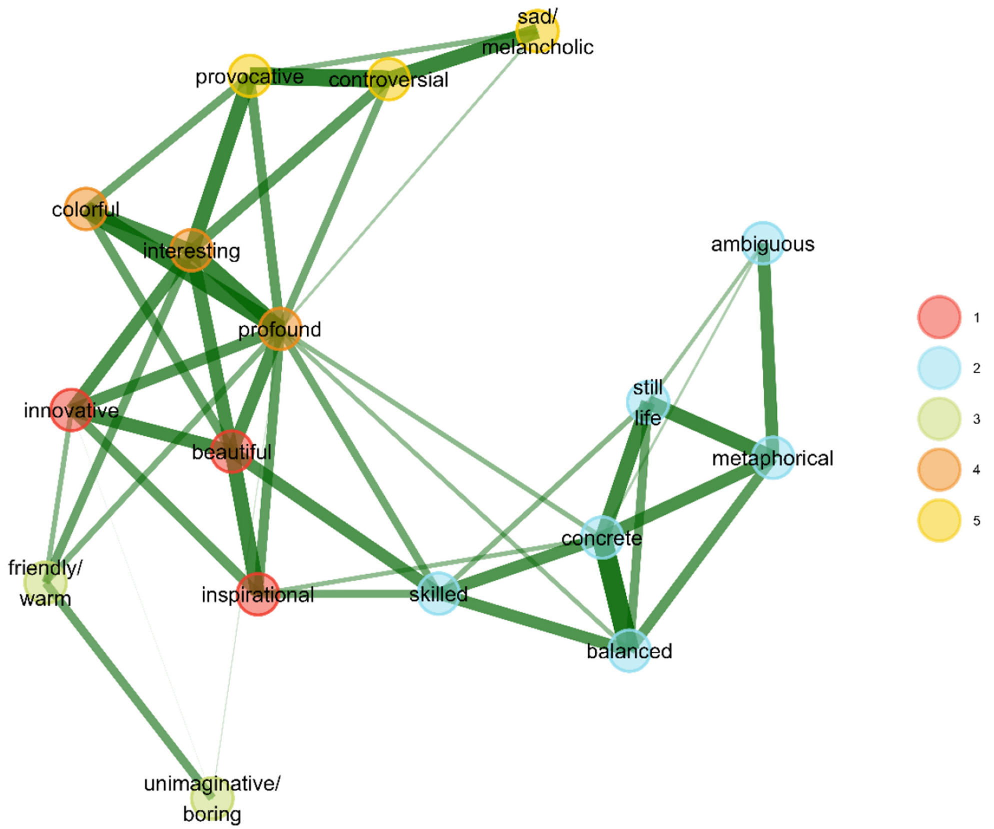

FIGURE 2 Higher order (coarse-grain) dimensions of the descriptive terms. Node label denotes lower order (fine-grain) dimension, node colour denotes higher order dimension, edge colour denotes positive (green) and negative (red) correlations, and edge size denotes size of correlation. Proximity of nodes depicts relative their relative position and semantic similarity.

dimension consists of terms people often associate with great art (beautiful, innovative, inspirational). The second higher order dimension is represented by terms related to an artwork's form and content (ambiguous, balanced, concrete, metaphorical, skilled, still life). The third dimension relates to qualities about an artwork's ease of processing that either invite or disengage a viewer (friendly/warm, unimaginative/boring). The fourth dimension relates to stimulating and positive qualities of artworks such as immersion, profundity and positive affect (colourful, interesting, profound) and is also aligned with the first dimension, that we think is associated with great art. In contrast, the fifth dimension relations to challenging and negative qualities of artworks (controversial, provocative, sad/melancholic).

There are a few higher order dimensions that are worth pointing out. Profundity was well connected to each of the higher order dimensions in the network suggesting it is highly related to many other descriptive features of artworks. This relative position suggests that profundity is closest to the conceptual core of the descriptive space. On the other hand, sad/melancholic and unimaginative/boring were weakly connected to other higher order dimensions suggesting that their relation to other descriptive terms are secondary.

Granularity of impact terms

The hierarchical EGA identified 11 lower order and 4 higher order dimensions of impact terms (Figures 3 and 4, respectively). For the lower order (fine-grain) dimensions, we report the three terms with the highest network loadings within their dimension and label the dimension by their highest network loading (separated by semi-colons with dimension label in italics): *angry/enraged*, offended, revolted/disgusted;

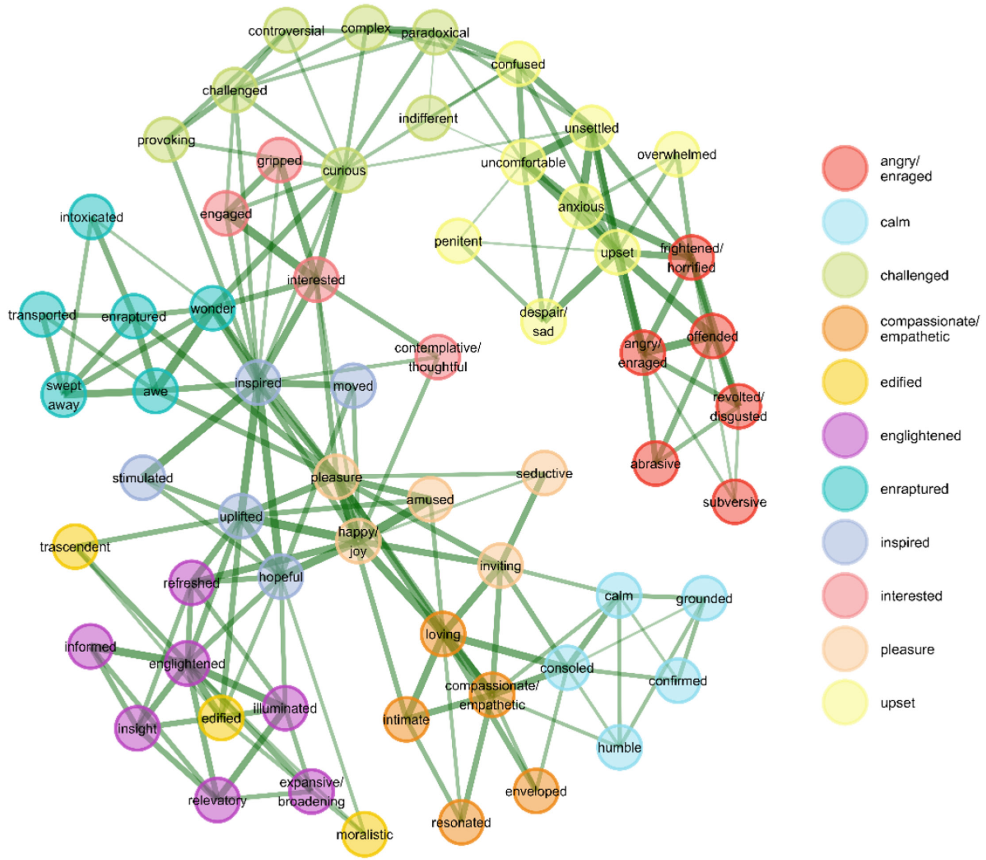

FIGURE 3 Lower order (fine-grain) dimensions of the impact terms. Node colour denotes lower order dimension, edge colour denotes positive (green) and negative (red) correlations, and edge size denotes size of correlation. Proximity of nodes depicts relative their relative position and semantic similarity.

calm, consoled, grounded; *challenged*, paradoxical, curious; *edified*, moralistic, transcendent; *enlightened*, illuminated, revelatory; *enraptured*, swept away, awe; *pleasure*, happy/joy, amused; *inspired*, hopeful, uplifted; *interested*, engaged, gripped; *compassionate/empathetic*, loving, intimate; *upset*, uncomfortable, unsettled (Figure 3).

The first higher order dimension of the impact terms consists of terms related to profound and immersive impacts (enraptured, interested). The second higher order dimension consists of terms related to positive affect (calm, compassionate/empathetic, pleasure), traversing low and high levels of arousal. The third dimension relates to challenging and negative affect impacts (angry/enraged, challenged, upset). The fourth dimension relates to impacts associated with transformation (edified, enlightened, inspired).

The higher order dimensions of interested and inspired were well connected with the rest of the dimensions and network suggesting these two themes are closest to the conceptual core of the impact semantic space. Further, both higher order dimensions were strongly related to pleasure suggesting that feeling interested and inspired is usually experienced positively. The higher order dimension of challenged has relatively contradictory relations where it is positively related to engaging with artwork (e.g. interested, inspired, enraptured), but also positively related to angry/enraged and upset. In contrast, interested and inspired are negatively related to angry/enraged and upset. These seemingly contradictory relationships of challenged seem to parallel the confusion-interest relationship where if a challenging artwork is not understood, then it leads to confusion; otherwise, understanding it leads to interest (Silvia, 2010).

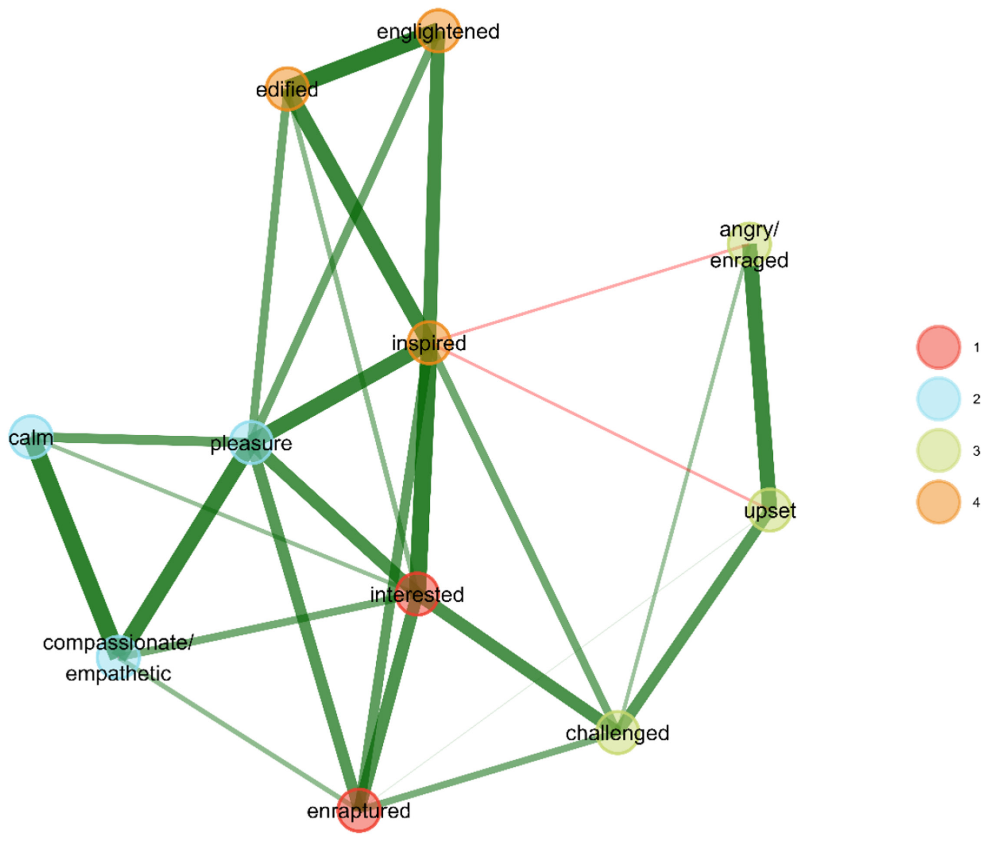

FIGURE 4 Higher order (coarse-grained) dimensions of the impact terms. Node label denotes lower order (fine-grain) dimension, node colour denotes higher order dimension, edge colour denotes positive (green) and negative (red) correlations, and edge size denotes size of correlation. Proximity of nodes depicts relative their relative position and semantic similarity.

DISCUSSION

The goal of this study was to establish a taxonomy of terms that is relevant to how people describe their engagement with art. Such a taxonomy is useful to design experiments to assess the impact that art can have on a viewer. Our study assumes that language plays an important mediating role in describing and appraising art. Importantly, our taxonomy reflects theoretical, rather than actual, responses and evaluations of an artwork. It represents a first step in establishing a common vocabulary that can be used to connect language used to describe impacts of art with actual experiences. In what follows, we describe our derivation of this taxonomy, its structural features, and how we think it is relevant and useful to advance research on the impacts of art.

Derivation of taxonomy

We started by recruiting an expert panel of art scholars to provide descriptive and impact terms related to experiences with art. This panel was comprised of experts from different disciplines to ensure that we captured a wide range of terms; terms that are not restricted by assumptions or scholarship in one discipline, such as psychology or philosophy. Using these terms, we obtained word associations from a general population to investigate how laypeople understand these terms and relate them to each other. We used network science methods to identify terms that were regarded similarly and to establish their taxonomic structure. These structures represent fine- and coarse-grained distinctions between terms that can be used to describe artworks and characterize their impacts on a viewer. In what follows, we describe these finer and coarser dimensions, discuss how they help identify the way people engage with art and suggest how the terms might be used prospectively in future studies.

For the terms used to describe art, we started with 124 terms generated by experts. This set was reduced to 113 terms, based on a local dependence analysis, suggesting that for non-experts, 11 pairs of terms had substantial semantic similarity. Using network analyses, we reduced these 113 terms into 17 fine-grain dimensions and then further reduced those into 5 coarse-grain dimensions. These reductions present trade-offs with both conceptual and practical implications. After reviewing our results of the descriptive and impact networks, we will return to the implications of these fine-coarse granularity trade-offs.

For the fine-grain network, our descriptive terms precipitated into 17 dimensions. These dimensions, if labelled by their most salient and sentinel terms are ambiguous, balanced, beautiful, colourful, concrete, controversial, friendly/warm, innovative, inspirational, interesting, metaphorical, profound, provocative, sad/melancholic, skilled, still-life and unimaginative/boring. At a coarser resolution, the largest of the five dimensions included terms that relate to the visual properties of artworks such as balanced, concrete and ambiguous (Chatterjee et al., 2010). These properties generally represent features of artworks that are descriptive and without assigned value. In contrast, the other dimensions at this coarse level reveal that descriptions of art seem to be laden with value. For example, colourful, interesting and profound formed one dimension. Colourful might be regarded as a purely descriptive term, but its association with interesting and profound suggest that this description of art in this context relates to its arousing nature. Examination of the fine-grained descriptors that colourful encompasses reveals the salience of its emotional, metaphorical senses rather than purely visual connotations (joyful/cheerful, exuberant, amusing, celebratory). Similarly, friendly/warm and unimaginative/boring as a dimension refers to a viewers' inclination to approach, perhaps at low levels of arousal or processing difficulty, traversing positive, negative and indifferent valence. Other dimensions, of beautiful, innovative and inspirational are positively valanced and arousing, while sad/melancholic, controversial and provocative are perhaps negatively valanced terms that extend from low to high arousal.

In deriving our art impact networks, we started with 81 terms from our expert panel. Based on the local dependence analysis, these were reduced to 61 terms. These terms organized into 11 finer-grained impact dimensions—angry/enraged, calm, challenged, compassionate/empathetic, edified, enlightened, enraptured, inspired, interested, pleasure, upset—which were then further reduced to 4 coarse-grained dimensions. At this coarser level, a single dimension related to difficult or negative impacts of art engagement (challenged, upset, angry/enraged). The other three dimensions to emerge related to positive outcomes of viewing art. The interested and enraptured dimension signals the importance of attentional engagement and immersion in the viewing experience. The calm, compassionate/empathetic and pleasure dimension captures positive affective responses to artworks, at both low and high levels of arousal. In contrast, the fourth dimension of edified, enlightened and inspired encompasses more cognitive and perhaps deeper impacts of art engagement.

Structural features of taxonomy

The higher order dimensions of the descriptive and impact terms provide broad, data-driven categories for how people understand the relationships between expert suggested terms related to art engagement. Nuances are reflected in the relationships (i.e. lines) between nodes and dimensions. For instance, in the higher order impact network, 'inspired' is positively associated with 'challenged', 'interested', 'pleasure', 'edified' and 'enlightened' but negatively associated with 'angry/enraged' and 'upset' (Figure 4). Although these dimensions, both at the lower and higher order, are discrete, we encourage researchers to also 'read-between-the-lines'. The interconnections between terms in the network represent their relationship within this semantic space. The dimensions represent discrete, emergent themes with edges between dimensions representing overlap between them. The edges between dimensions support a fuzzy interpretation. In addition, our terms do not represent all possible terms. More terms may exist within certain themes (e.g. ‘pedestrian’ in the lower order theme of unimaginative/boring in the descriptive network) and between themes (e.g. ‘frustrated’ between the terms ‘confused’ and ‘angry/upset’ in the lower order impact network). In general, the semantic space of descriptive and impact terms represent a nuanced semantic space of how artworks look and make people think and feel, with emergent fine- and coarse-grain themes that can be used to design future studies.

Depicted most centrally in the higher and lower order descriptive networks are terms with implications for ideas underpinning the ways that art can promote understanding.[1] These were the higher order dimensions comprised of colourful, interesting and profound dimensions. Reference to the fine-grained network reveals the qualities associated with these three dimensions, encompassing evaluations typically associated with artistic masterpieces (e.g. innovative and original; beautiful, impressive, amazing, sublime; inspired, inspirational, edifying, ambitious) and the spiritual content and meaning of art (e.g. religious/spiritual, metaphysical). These terms are often used to describe positive, impactful and transformative experiences with artworks (Pelowski et al., 2017).

At the coarse level of the impact network, we observed the dimension of edified, enlightened and inspired. Reference to the fine-grained network illuminates the cognitive nature of this dimension. Edified encompasses transcendent and moralistic, terms relevant to the transformative capacity of art and the type of knowledge it may convey. Enlightened subsumes fine-grained terms that speak to the potential of art to shift perspectives, convey new concepts or alter old ones (e.g. informed, insight, illuminated, revelatory, expansive/broadening). Inspired speaks to the capacity of art to stir or arouse its viewers from their pre-existing state, whether cognitively (stimulated) or emotionally (moved), and imagine a greater, more positive vantage point from which to understand human experience (hopeful, uplifted).

The finer-grained impact network also corroborated relationships between curious, interested and confusion, epistemic emotions with relevance for aesthetic cognitivism (Christensen, Cardillo, & Chatterjee, 2022). The confusion-interest relationship is well documented (Silvia, 2010). When people are not able to understand an artwork's intent or meaning, they can become confused and lose interest; in contrast, gaining insights about an artwork's intent or meaning can increase interest (Leder et al., 2004; Pelowski et al., 2017). Curiosity's position between confusion and interest may represent a precursor state, reflecting an initial desire to seek and learn more about an artwork (Berlyne, 1960, 1978). Whether expectations about the information that can be gained from an artwork are met can then shift to confusion or interest (Van de Cruys & Wagemans, 2011).

Many of the dimensions in our coarse descriptive network were congruent with the dimensions of the impact network. This convergence underscores the idea that viewers often infer and experience the artist's intended emotions conveyed in an artwork (Pelowski et al., 2020). Positive and negative affect, for example, were evident in both the descriptive and impact networks. Notably, the identification of dimensions relating to engagement (e.g. interesting/interested) and stimulation (e.g. inspirational/inspired) were not only present in both networks but were also most central to each network.

Although the structure and relations between terms corroborate the empirical literature, we emphasize that our discussion represents an initial exploration of the implications of this analysis. The empirical literature provides support for the validity of these relations and taxonomic structure; however, our study is limited in its generalizability beyond the relations between terms. Our goal was to establish a broad taxonomy that could be generalized to aesthetic experiences. However, we focused on visual art and no other arts like music or literature. This focus may limit the extent to which these terms and their emergent themes transfer to other aesthetic experiences. Presumably, different arts perhaps differ descriptively might have similar impacts. Similarly, our terms do not exhaust all possible impacts within the visual domain. While we started with experts from five different fields to ensure a wide range of input, a different group of experts might easily have suggested terms that were not in our initial set.

[1]Visual depictions of node's positions in a network are relative and may not accurately display the centrality of any node's position in the network (Jones et al., 2018). Quantitative evidence for these qualitative claims were confirmed by computing closeness centrality where larger values reflect shorter distances to all other nodes in the network (i.e. more central to the overall network). Closeness centrality was computed using the *NetworkToolbox* (version 1.4.3; Christensen, 2018) package in R.

Directions for future research

If one had a set of artworks, these images could be assessed for their potential impacts. Within empirical aesthetics, viewers are most often asked about whether they like an artwork or find it beautiful or interesting. Our taxonomy offers well-motivated reasons for querying a much wider range of impacts, such as whether the artwork makes a person feel calm, or enraged, or edified, or challenged.

Another direction for investigations based on this taxonomy is to identify a set of artworks that vary on these properties and impacts. Developing a stimulus set allows experimental manipulations of certain characteristics of artworks, which facilitate the systematic investigation into whether certain properties or impacts influence the acquisition of new knowledge and understanding. Importantly, our taxonomy is based on possible relationships and how these relationships translate to artwork-induced responses remains an open question. This taxonomy can be used as common vocabulary and motivate theory-driven approaches examining artwork-induced experiences. Gathering empirical evidence of these relationships is a necessary step to establish a stimulus set of artworks that vary on the dimensions identified in our taxonomy.

Once established, how might such a catalogue of artwork and their potential impacts be used for experimental studies? Using a dimensional approach based on our findings would allow researchers to avoid one vexing problem in experimental design—that is, establishing a proper control condition. Since defining art itself is problematic (Chatterjee, 2014), identifying non-art as a control comparison becomes near impossible. Rather than framing the question of what is the impact of art, which would require also assessing the impact of non-art, one could ask how does art produce disgust and under what conditions is a disgust response also interesting versus when it makes the viewer uncomfortable? Similarly, mining the relationships within a network: say, how expertise might modulate whether artworks with challenging, upsetting and angry/enraging impacts also have edifying, enlightening and inspired impacts. Once each painting is normed along these dimensions, investigators could pick stimuli based on how these specific dimensions vary parametrically to address their question.

Future studies could leverage the taxonomy to investigate whether people are impacted differently based on where they interact with the artwork. Several studies demonstrate that artworks experienced in a museum setting elicit greater satisfaction (Cotter et al., 2021) and range of emotions (Rodriguez-Boerwinkle et al., 2021) as well as a motivation to seek new information (Trainer et al., 2012) and more challenging artworks (Muth et al., 2017). Evaluating whether museums or other natural art environments (e.g. murals on the street, dance or musical performance in a theatre) increase the impact artworks have on people will clarify their role in promoting new knowledge and understanding from art (Christensen, Cardillo, & Chatterjee, 2022).

This study represents a first step towards empirically investigating aesthetic cognitivism by developing a taxonomy of artwork descriptions and impacts. This taxonomy provides a useful structure to organize appraisals of artworks and experiences that might lead to new understanding, from propositional knowledge to personally transformative perspective shifts or spiritual insights. Understanding how people gain new understanding can be elaborated in the dynamics of these experiences, allowing for more targeted investigations into specific outcomes (e.g. confusion-interest). Fundamental to investigating aesthetic cognitivism is the assessment of the knowledge content or conceptual understanding that is reportedly gained (Christensen, Cardillo, & Chatterjee, 2022). Our taxonomy provides a common language for researchers and laypeople to use and express their experiences when engaging with art, providing a basis to communicate factors contributing to knowledge acquisition. By grounding aesthetic cognitivism in language, researchers can generate testable hypotheses about how art advances understanding and assess the nature of that understanding.

AUTHOR CONTRIBUTIONS

Alexander Christensen: Conceptualization; data curation; formal analysis; investigation; methodology; project administration; resources; software; validation; visualization; writing – original draft; writing – review and editing. **Eileen R. Cardillo:** Conceptualization; data curation; funding acquisition;

investigation; methodology; resources; validation; writing – review and editing. **Anjan Chatterjee:** Conceptualization; data curation; funding acquisition; investigation; methodology; resources; supervision; validation; writing – review and editing.

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CONFLICT OF INTEREST

The authors declare that there are no conflict of interest.

DATA AVAILABILITY STATEMENT

All data and R scripts used to preprocess and analyse the data are available on our OSF page.

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REFERENCES

Asparouhov, T., & Muthén, B. (2009). Exploratory structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, *16*(3), 397–438. https://doi.org/10.1080/10705510903008204

Baumberger, C. (2013). Art and understanding: In defence of aesthetic cognitivism. *PhilPapers*. https://philpapers.org/rec/BAUAAU-2

Berlyne, D. E. (1960). The new experimental aesthetics. In D. E. Berlyne (Ed.), *Studies in the new experimental aesthetics* (pp. 1–25). Hemisphere Publication Services.

Berlyne, D. E. (1978). Curiosity and learning. *Motivation and Emotion*, *2*, 97–175. https://doi.org/10.1007/BF00993037

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, *2008*(10), P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008

Burke, E. (1958). In J. T. Boulton (Ed.), *A philosophical enquiry into the origin of our ideas of the sublime and beautiful*. Routledge & Kegan Paul. (Original work published 1759). https://doi.org/10.7312/burk90112

Chatterjee, A. (2014). *The aesthetic brain: How we evolved to desire beauty and enjoy art*. Oxford University Press.

Chatterjee, A., Widick, P., Sternschein, R., Smith, W. B., II, & Bromberger, B. (2010). The assessment of art attributes. *Empirical Studies of the Arts*, *28*(2), 207–222. https://doi.org/10.2190/EM.28.2.f

Christensen, A. P. (2018). NetworkToolbox: Methods and measures for brain, cognitive, and psychometric network analysis in R. *The R Journal*, *10*(2), 422–439. https://doi.org/10.32614/RJ-2018-065

Christensen, A. P., Cardillo, E. R., & Chatterjee, A. (2022). Can art promote understanding? A review of the psychology and neuroscience of aesthetic cognitivism. *PsyArXiv*. https://doi.org/10.31234/osf.io/t8c47

Christensen, A. P., Garrido, L. E., & Golino, H. (2021). Comparing community detection algorithms in psychological data: A Monte Carlo simulation. *PsyArXiv*. https://doi.org/10.31234/osf.io/hz89e

Christensen, A. P., Garrido, L. E., & Golino, H. (2022). Unique variable analysis: A network psychometrics method to detect local dependence. *PsyArXiv*. https://doi.org/10.31234/osf.io/4kra2

Christensen, A. P., & Golino, H. (2021). On the equivalency of factor and network loadings. *Behavior Research Methods*, *53*(4), 1563–1580. https://doi.org/10.3758/s13428-020-01500-6

Christensen, A. P., & Kenett, Y. N. (2021). Semantic network analysis (SemNA): A tutorial on preprocessing, estimating, and analyzing semantic networks. *Psychological Methods*. Advance online publication. https://doi.org/10.1037/met0000463

Cotter, K. N., Chen, D. F., Christensen, A. P., Kim, K. Y., & Silvia, P. J. (2021). Measuring art knowledge: Item response theory and differential item functioning analysis of the aesthetic fluency scale. *Psychology of Aesthetics, Creativity, and the Arts*. Advance online publication. https://doi.org/10.1037/aca0000397

Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal, Complex Systems*, *1695*(5), 1–9.

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

Fayn, K., Silvia, P. J., Erbas, Y., Tiliopoulos, N., & Kuppens, P. (2018). Nuanced aesthetic emotions: Emotion differentiation is related to knowledge of the arts and curiosity. *Cognition and Emotion*, *32*(3), 593–599. https://doi.org/10.1080/02699931.2017.1322554

Fortunato, S. (2010). Community detection in graphs. *Physics Reports*, *486*(3–5), 75–174. https://doi.org/10.1016/j.physrep.2009.11.002

Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, *9*, 432–441. https://doi.org/10.1093/biostatistics/kxm045

Golino, H., & Christensen, A. P. (2022). EGAnet: Exploratory graph analysis – A framework for estimating the number of dimensions in multivariate data using network psychometrics. https://CRAN.R-project.org/package=EGAnet

Golino, H., Christensen, A. P., Moulder, R., Kim, S., & Boker, S. M. (2021). Modeling Latent Topics in Social Media using Dynamic Exploratory Graph Analysis: The Case of the Right-wing and Left-wing Trolls in the 2016 US Elections. *Psychometrika*, *87*(1), 156–187. https://doi.org/10.1007/s11336-021-09820-y

Golino, H., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PLoS One*, *12*(6), e0174035. https://doi.org/10.1371/journal.pone.0174035

Golino, H., Shi, D., Christensen, A. P., Garrido, L. E., Nieto, M. D., Sadana, R., Thiyagarajan, J. A., & Martinez-Molina, A. (2020). Investigating the performance of exploratory graph analysis and traditional techniques to identify the number of latent factors: A simulation and tutorial. *Psychological Methods*, *25*(3), 292–320. https://doi.org/10.1037/met0000255

Goodman, N. (1968). *Languages of art: An approach to a theory of symbols*. Bobbs-Merril.

Hayn-Leichsenring, G. U., Kenett, Y. N., Schulz, K., & Chatterjee, A. (2020). Abstract art paintings, global image properties, and verbal descriptions: An empirical and computational investigation. *Acta Psychologica*, *202*, 102936. https://doi.org/10.1016/j.actpsy.2019.102936

Hidi, S. E., & Renninger, K. A. (2020). On educating, curiosity, and interest development. *Current Opinion in Behavioral Sciences*, *35*, 99–103. https://doi.org/10.1016/j.cobeha.2020.08.002

Jiménez, M., Abad, F. J., Garcia-Garzon, E., Golino, H., Christensen, A. P., & Garrido, L. E. (2022). Dimensionality assessment in generalized bi-factor structures: A network psychometrics approach. *PsyArXiv*. https://doi.org/10.31234/osf.io/2ujdk

Jones, P. J., Mair, P., & McNally, R. J. (2018). Visualizing psychological networks: A tutorial in R. *Frontiers in Psychology*, *9*, 1742. https://doi.org/10.3389/fpsyg.2018.01742

Kant, I. (1986). *Critique of judgment* (W. S. Pluhar Trans.). Hackett Publishing. (Original work published 1790).

Kenett, Y. N., Kenett, D. Y., Ben-Jacob, E., & Faust, M. (2011). Global and local features of semantic networks: Evidence from the Hebrew mental lexicon. *PLoS One*, *6*(8), e23912. https://doi.org/10.1371/journal.pone.0023912

Lancichinetti, A., & Fortunato, S. (2012). Consensus clustering in complex networks. *Scientific Reports*, *2*(1), 1–7. https://doi.org/10.1038/srep00336

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

Leising, D., Burger, J., Zimmermann, J., Bäckström, M., Oltmanns, J. R., & Connelly, B. S. (2020). Why do items correlate with one another? A conceptual analysis with relevance for general factors and network models. *PsyArXiv*. https://doi.org/10.31234/osf.io/7c895

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. https://doi.org/10.3389/fpsyg.2016.00973

Massara, G. P., Di Matteo, T., & Aste, T. (2017). Network filtering for big data: Triangulated maximally filtered graph. *Journal of Complex Networks*, *5*(2), 161–178. https://doi.org/10.1093/comnet/cnw015

Menninghaus, W., Wagner, V., Wassiliwizky, E., Schindler, I., Hanich, J., Jacobsen, T., & Koelsch, S. (2019). What are aesthetic emotions? *Psychological Review*, *126*(2), 171–195. https://doi.org/10.1037/rev0000135

Muth, C., Hesslinger, V. M., & Carbon, C. C. (2015). The appeal of challenge in the perception of art: How ambiguity, and the opportunity for insight affect appreciation. *Psychology of Aesthetics, Creativity, and the Arts*, *9*(3), 206–216. https://doi.org/10.1037/a0038814

Muth, C., Raab, M. H., & Carbon, C.-C. (2017). Expecting the unexpected: How gallery visitors experience semantic instability in art. *Art & Perception*, *5*(2), 121–142. https://doi.org/10.1163/22134913-00002062

Newman, M. E. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences*, *103*(23), 8577–8582. https://doi.org/10.1073/pnas.0601602103

Pelowski, M. (2015). Tears and transformation: Feeling like crying as an indicator of insightful or "aesthetic" experience with art. *Frontiers in Psychology*, *6*, 1006. https://doi.org/10.3389/fpsyg.2015.01006

Pelowski, M., Hur, Y.-J., Cotter, K. N., Ishizu, T., Christensen, A. P., Leder, H., & McManus, I. C. (2021). Quantifying the if, the when, and the what of the sublime: A survey and latent class analysis of incidence, emotions, and distinct varieties of personal sublime experiences. *Psychology of Aesthetics, Creativity, and the Arts*, *15*(2), 216–240. https://doi.org/10.1037/aca0000273

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

Pelowski, M., Specker, E., Gerger, G., Leder, H., & Weingarden, L. S. (2020). Do you feel like I do? A study of spontaneous and deliberate emotion sharing and understanding between artists and perceivers of installation art. *Psychology of Aesthetics, Creativity, and the Arts*, *14*(3), 276–293. https://doi.org/10.1037/aca0000201

R Core Team. (2022). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Retrieved from https://www.R-project.org/

Renninger, K. A., & Hidi, S. E. (2020). To level the playing field, develop interest. *Policy Insights From the Behavioral and Brain Sciences*, *7*(1), 10–18. https://doi.org/10.1177/2372732219864705

Rodriguez-Boerwinkle, R. M., Fekete, A., Silvia, P. J., & Cotter, K. N. (2021). The art of feeling different: Measuring and exploring the diversity of emotions experienced during a museum visit. *PsyArXiv*. https://doi.org/10.31234/osf.io/f7g5a

Schindler, I., Hosoya, G., Menninghaus, W., Beermann, U., Wagner, V., Eid, M., & Scherer, K. R. (2017). Measuring aesthetic emotions: A review of the literature and a new assessment tool. *PLoS One*, *12*(6), e0178899. https://doi.org/10.1371/journal.pone.0178899

Schloerke, B., Cook, D., Larmarange, J., Briatte, F., Marbach, M., Thoen, E., Elberg, A., & Crowley, J. (2021). GGally: Extension to 'ggplot2'. https://CRAN.R-project.org/package=GGally

Silvia, P. J. (2010). Confusion and interest: The role of knowledge emotions in aesthetic experience. *Psychology of Aesthetics, Creativity, and the Arts*, *4*(2), 75–80. https://doi.org/10.1037/a0017081

Skov, M., & Nadal, M. (2020). There are no aesthetic emotions: Comment on Menninghaus et al. (2019). *Psychological Review*, *127*(4), 640–649. https://doi.org/10.1037/rev0000187

Song, W. M., Di Matteo, T., & Aste, T. (2012). Hierarchical information clustering by means of topologically embedded graphs. *PLoS One*, *7*(3), e31929. https://doi.org/10.1371/journal.pone.0031929

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*, e0232083. https://doi.org/10.1371/journal.pone.0232083

Specker, E., Forster, M., Brinkmann, H., Boddy, J., Pelowski, M., Rosenberg, R., & Leder, H. (2020). The Vienna art interest and art knowledge questionnaire (VAIAK): A unified and validated measure of art interest and art knowledge. *Psychology of Aesthetics, Creativity, and the Arts*, *14*(2), 172–185. https://doi.org/10.1037/aca0000205

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*, 47–53. https://doi.org/10.1016/j.actpsy.2018.04.007

Specker, E., Leder, H., & Zwaan, R. (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

Stolnitz, J. (1992). On the cognitive triviality of art. *The British Journal of Aesthetics*, *32*(3), 191–200. https://doi.org/10.1093/bjaesthetics/32.3.191

Trainer, L., Steele-Inama, M., & Christopher, A. (2012). Uncovering visitor identity: A citywide utilization of the Falk visitor-identity model. *Journal of Museum Education*, *37*(1), 101–114. https://doi.org/10.1080/10598650.2012.11510722

Van de Cruys, S., & Wagemans, J. (2011). Putting reward in art: A tentative prediction error account of visual art. *i-Perception*, *2*(9), 1035–1062. https://doi.org/10.1068/i0466aap

Vogl, E., Pekrun, R., Murayama, K., & Loderer, K. (2020). Surprised–curious–confused: Epistemic emotions and knowledge exploration. *Emotion*, *20*(4), 625–641. https://doi.org/10.1037/emo0000578

Wassiliwizky, E., & Menninghaus, W. (2021). Why and how should cognitive science care about aesthetics? *Trends in Cognitive Sciences*, *25*(6), 437–449. https://doi.org/10.1016/j.tics.2021.03.008

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis*. Springer-Verlag. https://ggplot2.tidyverse.org

Zhang, B., & Horvath, S. (2005). A general framework for weighted gene co-expression network analysis. *Statistical Applications in Genetics and Molecular Biology*, *4*(1), 17. https://doi.org/10.2202/1544-6115.1128

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