

An exploratory semantic clustering study of how people describe AI art: Implications for psychotherapy

Alexandru Popescu^{a,*}, Andreea Huțul^{a,b}, Tudor-Daniel Huțul^{a,b}, Andrei Corneliu Holman^a

^a Alexandru Ioan Cuza University of Iași, Department of Psychology, Faculty of Psychology and Education Sciences, Romania

^b Department of Communication and Social Research, Sapienza University of Rome, Italy

ARTICLE INFO

Dataset link: <https://osf.io/rhk8f/overview>

Keywords:

Mental representations
Artificial intelligence
Human-AI interaction
Aesthetics
Attitudes towards artificial intelligence

ABSTRACT

The emergence of Artificial Intelligence (AI) art challenges established aesthetic frameworks, frequently resulting in a documented negative bias when non-human authorship is known. This exploratory study investigated the cognitive schemas activated by traditional visual art and AI art, and how these mental representations are shaped by individual attitudes towards AI. Using the free association technique, 560 participants provided three descriptive words for both art forms, which were subsequently quantified using word embeddings. Principal Component Analysis (PCA) revealed a significant semantic distinction between the vocabularies used for the two art types, with specific clusters emerging for both art forms. These clusters emphasize that traditional visual art is thought of in terms of emotionality and expressiveness, the creative process, aesthetic beauty, color, and art forms and styles which can express the aforementioned dimensions, while AI art is centered on technological innovation, novelty, artificiality, lack of emotion and authenticity, and themes related to fake and stolen content. Additionally, positive attitudes toward AI were associated with greater use of positive AI-related words and reduced use of negative terms. Alternatively, positive AI attitudes negatively predicted the use of traditional art words related to emotion and expressiveness and the creative process. These findings show that AI art activates a more ambivalent and technologically oriented schema compared to the predominantly positive, emotionally grounded schema of traditional art. We discuss these findings in terms of their implications for psychotherapy and how AI-generated imagery may differ from traditional creative expression in therapeutic contexts.

1. Introduction

Humans have maintained a close relationship with visual art that stretches back tens of thousands of years in our history. Some of the earliest known examples include hand stencils found in 11 caves in Spain, dating back to at least 40,800 years (Pike et al., 2012), and the depiction of a warty pig on the walls of the Leang Tedongnge cave in Indonesia, dating back 45,500 years (Brumm et al., 2021). From an evolutionary perspective, engagement with visual art, alongside the emergence of language, contributed to the development of symbolic and abstract cognition, which are two key components of how humans think (Zaidel, 2010).

Building on this connection, research shows that visual art continues to play an important role in human life, not only culturally, but

psychologically as well (Magsamen, 2019). Creating visual art and engaging with it has multiple beneficial psychological impacts, such as increasing overall well-being (Mastandrea et al., 2019; Trupp et al., 2023, 2025) and decreasing stress (Law et al., 2021; Tjasink et al., 2023). In clinical populations, art therapy has been shown to yield positive outcomes for mental disorders such as depression (Jenabi et al., 2023) and anxiety (Zhang et al., 2024), as well as for cognitive impairments and conditions, such as dementias, Alzheimer's disease, schizophrenia, and autism (Hu et al., 2021).

Given the evolutionary and psychological importance of visual art, cultural shifts that challenge its definition become especially meaningful. Today, such a shift is occurring with the advent of artificial intelligence (AI) and its ability to generate images that closely resemble what we traditionally call art. A frequent claim is that "AI generated images

* Corresponding author. Department of Psychology, Faculty of Psychology and Education Sciences, Alexandru Ioan Cuza University of Iași, 3 Toma Cozma Street, 700554, Iași, Romania.

E-mail addresses: alex.popescu.official@gmail.com (A. Popescu), andreeahutulpsih@gmail.com (A. Huțul), tudordanielhutulpsih@gmail.com (T.-D. Huțul), andrei.holman@uaic.ro (A.C. Holman).

<https://doi.org/10.1016/j.newideapsych.2026.101269>

Received 31 March 2026; Received in revised form 14 May 2026; Accepted 24 May 2026

Available online 27 May 2026

0732-118X/© 2026 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

are not art" (Horton Jr et al., 2023). Thus, what characteristics guide people to classify an object as art, and which of these characteristics are infringed upon by AI art? The research literature already highlighted how AI challenges several core human attributes of art, such as creativity (García, 2024; Grilli & Pedota, 2024; Rafner et al., 2023), agency (Mikalonytė & Kneer, 2022), and authenticity (Pelowski, Forster, et al., 2017). Research also highlights that people tend to think more negatively of AI art in terms of aesthetic appreciation (Bellaiche et al., 2023; Neef et al., 2024) and emotional impact (Millet et al., 2023), which might hinder the positive effect visual art has on individuals, for example, when used as a psychotherapeutic tool. Using AI art during psychotherapy could lead to a loss of agency for both the clients and therapists (Zubala et al., 2025), which is pivotal to the therapeutic alliance and positive therapy outcomes (Coleman & Neimeyer, 2015; Huber et al., 2021).

1.1. Difficulties in defining what is art

Defining what is art is a difficult task, due to numerous philosophical, psychological and artistic perspectives (Isrow, 2017). The Merriam-Webster Dictionary defines art as the conscious use of skill and creative imagination especially in the production of aesthetic objects (Merriam-Webster, 2025), highlighting that art is inherently human due to the need of conscious decision when creating it. Many authors also support this idea, suggesting that perceiving an object as art is one of the few uniquely human phenomena (Leder et al., 2012; Pelowski, Forster, et al., 2017; Y. Wang & Ma, 2019, pp. 445–449). In turn, art created by machines or artificial intelligence is not considered art because it lacks consciousness (Coeckelbergh, 2017).

This difficulty complicates the study of how people appraise and interact with art (Leder et al., 2004), due to the confusion regarding what participants in these studies find to be art or not. Everyday objects are appraised differently when presented in an artistic context rather than a regular, day to day context (Iosifyan & Wolfe, 2024; Pelowski, Gerger, et al., 2017), creating uncertainty when differentiating an ordinary object from a piece of art (Hayn-Leichsenring, 2017). Even amongst established art currents, some are viewed more as art than others. For example, despite being shown artworks originating from highly regarded artistic currents such as renaissance, baroque, abstract or hyperrealism, some people found hyperrealistic paintings and readymade sculptures to not be art (Pelowski, Gerger, et al., 2017).

Mikalonytė and Kneer (2024) argue that people without art expertise base their concept of art on three criteria: aesthetic value, intentional creation, and institutional recognition, with aesthetic value being the most important. However, institutional recognition can compensate when beauty is lacking. Similarly, unintentionally produced but aesthetically pleasing paintings may still be considered art, even if their creators are not regarded as artists (Mikalonytė & Kneer, 2024). Further complexity in defining art arises from the fact that aesthetic judgements are not universally valid (Cova & Pain, 2012), which means that an artistic object may be considered aesthetically pleasing by some and unpleasing by others. Another perspective proposes that for an object to be classified as art, it needs to either express excellence of skill and achievement, to fall under a publicly recognized art genre or to be intended by its creator to be art, with greater emphasis being put on the latter two aspects (Davies, 2015).

1.2. Psychological mechanisms of art evaluation

Aesthetic evaluation includes both cognitive control to appraise the object and the perception of the artwork's properties (Cupchik et al., 2009). As such, the resulting aesthetic evaluation consists of a mix of bottom-up processes, which are stimulus-driven, and top-down processes, which are perceiver-driven (Callaway et al., 2023; Chamberlain, 2022; Goetz & Carbon, 2023; Hosoya, 2020; Leder et al., 2012; Papenmeier et al., 2024). On one hand, studies demonstrate that

inherent characteristics of stimuli significantly influence their processing and evaluation. For example, people tend to prefer visual art that is easy to process and fluent (Belke et al., 2010), symmetric (Jacobsen & Höfel, 2002), repetitive (Forsythe et al., 2011), or of medium complexity (Berlyne, 1970; Grzywacz & Aleem, 2022).

However, the interpretation of the stimuli also plays a significant role in shaping evaluations, balancing the perceptual appraisal. In some instances, emotions elicited by art have a greater impact on liking ratings compared to their perceptual characteristics (Reynolds & Ricciardi, 2024). Research also shows that people prefer artworks that are accompanied by elaborative and easy to pronounce titles (Anglada-Tort et al., 2019; Gerger & Leder, 2015), when they are viewed in a specific context, such as a museum or art gallery (Brieber et al., 2015; Darda & Chatterjee, 2023; Gerger et al., 2014; Grüner et al., 2019; Pelowski, Forster, et al., 2017; Specker et al., 2017; Szubielska & Imbir, 2021), when they are experienced in a social context (Altenmüller & Plewe, 2024; Pelowski, Forster, et al., 2017) or if the artworks were previously evaluated by peers (Lauring et al., 2016).

Another aspect modulating aesthetic evaluation of artworks is information about the author, as some view artworks as extensions of the artist (Newman & Smith, 2018). Research shows that informing participants that an artwork was made by or by a famous artist (Mastandrea & Crano, 2019) or a professional artist instead of the experimenters (Kirk et al., 2009) leads to a more favorable evaluation of the artwork. Additionally, artworks perceived as having high artistic value are liked more and attract a higher willingness to pay for them (Spee et al., 2022). This effect was observed with AI art as well: knowing that the artwork was created by a non-human agent results in more negative aesthetic evaluations in terms of liking, beauty, interest, authenticity, and creativity (Chamberlain et al., 2018; Chiarella et al., 2022; Darewych, 2023). This devaluation mechanism function implicitly and unconsciously (Zhou & Kawabata, 2023).

Lastly, when engaging with artworks, viewers experience a plethora of emotions, both positive and negative (Bruder & Uck, 2000; Hoshi et al., 2025; Tinio & Gartus, 2018) that extend beyond pleasantness or unpleasantness. Amongst these emotions we find psychedelic, mysterious, disgusting or disorienting (Stamkou et al., 2024). Emotions felt in relation to art are often referred to as aesthetic emotions (Kuchinke et al., 2009), and they affect how the artwork is perceived (Reynolds & Ricciardi, 2024). For example, scholars argue that aesthetic experiences arise from emotional and bodily engagement with the artwork (Brinck, 2018). People experience more positive (Samo & Highhouse, 2023) and intense emotions (Demmer et al., 2023) when viewing art made by humans than in relation to AI art. However, emotions felt when engaging with AI art can also include positive emotions, such as surprise, excitement, and curiosity (Chen & Ibrahim, 2023), besides negative emotions, such as discomfort (Agudo et al., 2022) and anxiety (C. Wang & Xiao, 2025). This suggests that traditional visual art is experienced predominantly positively, while AI art is experienced ambivalently.

1.3. Cognitive schema of visual art

Even before interacting with an object, people direct their behavior based on previous experience and expectations (Pelowski & Akiba, 2011). In seeing an object as art, individuals adopt an aesthetic attitude (Westerman, 2018). As previously argued, aesthetic experiences are not shaped purely by visual or sensory appraisals; they are meaning-driven (Leder et al., 2004). These expectations and experiences form a cognitive schema, which in turn shapes how individuals interact with artistic stimuli (Pelowski & Akiba, 2011; Wagner et al., 2014). In the case of visual art, some important components of the cognitive schema are authenticity (Huang et al., 2011; Newman & Bloom, 2012), emotions (Leder et al., 2014; van Paasschen et al., 2015) and authorship (Di Dio et al., 2023). Research shows that original pieces tend to be valued more than identical copies (Newman & Bloom, 2012; Rabb et al., 2018; Wolz & Carbon, 2014), that visual art elicits immediate affective

responses measurable at a neural level (Cheung et al., 2019; Else et al., 2015) and artworks accompanied by negative biographical information about an artist received a reduced aesthetic appreciation (Kaube & Abdel Rahman, 2024). As such, activating the art schema in a viewer results in changes in aesthetic evaluation of the object. Knowing that an artistic object was created by AI may lead to decreases in aesthetic appraisals, including ratings of beauty, interest, and authenticity (Darewych, 2023).

1.4. AI art evaluation

We are witnesses to a shift in how people interact with artificial intelligence when it comes to art, not only a technological level, but on a cultural level as well (Garcia, 2024). Artificial intelligence (AI) is comprised of the algorithms that enable computers to imitate behavior similar to that of humans (Mondal, 2020; Russell & Norvig, 2020), spanning a wide range of applications such as having a conversation (Hill et al., 2015), and assisting during surgeries (Hassan et al., 2023).

AI is also widely used in a range of creative applications as well, such as content creation and enhancing, information analysis, extraction and enhancement, ranging from images to music and animation (Anantrasirichai & Bull, 2022; Choi et al., 2021). Although AI may produce aesthetically beautiful artworks, these can lack human-like intention or institutional status (Bellaiche et al., 2023). It is also difficult to argue that the human controlling the machine is the author of the machine's output (Epstein et al., 2020). Some authors view AI as merely a tool in the creative process (Epstein et al., 2020), while others argue that the authorship of an image is distributed between the AI algorithm and the human overseeing it (Goodfellow, 2024).

Since AI lacks the conscious decision making which is present in humans when creating art, scholars argue that it is impossible for AI art to be authentic (Aris et al., 2023). Although AI art could be indistinguishable from human-made art (Di Dio et al., 2023; Park et al., 2023), and may be similarly perceived in some evaluations (Samo & Highhouse, 2023), the knowledge that the artwork was created by AI can activate a different framing, that significantly differs from that of human-made art (Bara et al., 2025). As a result, viewers may experience less positive emotions (Samo & Highhouse, 2023) and reduced aesthetic appraisals (Chiarella et al., 2022). Research indicates that people exclude works created by AI from the category of human-made art and, as such, apply different standards when evaluating it (Fortuna & Modliński, 2021). These standards can lay the foundation of a cognitive schema by which people find AI incapable of creating art (Hong & Curran, 2019).

1.5. The current study

The current exploratory study aims to observe people's cognitive schemas that are activated when describing traditional visual art and AI art, in order to better understand the underlying cognitive representations reflected in how people tend to aesthetically evaluate AI art more negatively than art created by humans. People use a large variety of words to describe visual art. While "beauty" is the most predominant descriptor, other words such as "original", "dreamy", or "colorful" are also frequently used (Augustin, Carbon, & Wagemans, 2012; Augustin, Wagemans, & Carbon, 2012), suggesting that the cognitive schema of art is activated by a broader spectrum of words, beyond the most commonly used. This highlights a more sophisticated view of visual art, that guides people in their classification of an object as art or non-art, and provides a discussion point for better understanding AI art, which unlike traditional art, tends to evoke feelings of artificiality and novelty (Hattori et al., 2024; Salas Espasa & Camacho, 2025), or ethical concerns (Brewer et al., 2025).

Its findings may offer researchers a foundation for their future investigations on people's evaluation of AI art in comparison to traditional visual art. Research has already highlighted that people value creativity

(Millet et al., 2023), authenticity (Newman & Bloom, 2012), intentionality (Agüera y Arcas, 2017), and positive emotionality (Samo & Highhouse, 2023) when viewing traditional visual art, but there might be other latent characteristics still to be uncovered (Mikalonytė & Kneer, 2023). People feel that AI art lacks the aforementioned aspects, and thus, they deny that AI outputs can even be considered art (Kraatz & Xie, 2023). We thus hypothesize that people will use different verbiage to describe traditional visual art and AI art, and that the words they use would cluster around specific themes that are representative of the broader concept.

Additionally, we are interested in how attitudes toward artificial intelligence shape cognitive representations of art and influence word usage. We therefore hypothesize that word use would be significantly affected by general attitudes toward artificial intelligence, such that more positive attitudes would be associated with more positive and fewer negative terms.

2. Method

2.1. Participants and procedure

A total of 560 participants aged between 18 and 57 years ($M = 23.1$, $SD = 7.36$) took part in this study, which were recruited using the snowball sampling technique (Parker et al., 2019). The majority were female (77.32%), residing in the urban area (63.57%), and having ongoing university studies (48.21%). Participants' demographic characteristics are detailed in Table 1.

Prior to data collection, a priori power analyses were conducted to ensure an adequate sample size. Power calculation was done using G*Power 3.1 (Faul et al., 2009). For correlation analyses, in order to detect a small to medium effect size ($r = 0.30$), at a power level of 0.80 and a significance level of 0.05, a minimum of 82 participants was required, while for a logistic regression with 3 predictors, in order to detect a small to medium effect size ($OR = 1.30$), at a power level of 0.80 and a significance level of 0.05, a minimum of 372 participants was required. Our final sample size of 560 participants exceeds these requirements, providing adequate power and more accurate estimates (Lakens, 2022).

Data were collected through a Google Forms questionnaire distributed both in person and digitally via general faculty Facebook groups.

Table 1
Demographic characteristics of the participants (N = 560).

Characteristics	Category	N	%
Gender	Male	123	21.96
	Female	433	77.32
	Non-binary	4	0.71
Provenience	Urban	356	63.57
	Rural	204	36.43
Studies	Pre-university studies	202	36.07
	Ongoing university studies	270	48.21
	Postgraduate studies	88	15.71
Marital status	Single	221	39.46
	In a relationship	273	48.75
	Married	65	11.61
	Divorced	1	0.18
Income	Below 2000 lei/month	236	42.14
	Between 2000 and 5000 lei/month	140	25.00
	Above 5000 lei/month	61	10.89
	Do not want to disclose	123	21.96
Religion	Orthodox Christian	423	75.54
	Catholic Christian	41	7.32
	Agnostic/atheist	64	11.43
	Protestant	16	2.86
	Do not want to disclose	8	1.43
	None of the above	8	1.43

To prevent participants from submitting multiple responses, the questionnaire was configured to limit submissions to one response per participant. No email addresses were collected, and participation was therefore 100% anonymous. The study was approved by the Research Ethics Committee of the authors' faculty (No. 1636/18.09.2025), and informed consent was obtained before participation. Participants first completed demographic questions, followed by items assessing their experience with visual art, passion for art, and beliefs about whether AI can create art. They were then asked to provide three words or ideas associated with traditional visual art and AI art, respectively. Finally, participants completed the Artificial Intelligence Attitude Scale (AIAS-4; Grassini, 2023), and then submitted their response.

2.2. Measures

Art Cognitive Schema: To assess participants' cognitive schemas of art, we used the free association method. Each participant was asked to write down the first, second and third word or phrase that comes to mind in regards to the prompts "traditional visual art" and "visual art created by artificial intelligence". The free association method is a direct way to access the participants' conceptual categories without requiring enormous rational processing (Kuska et al., 2016). Additionally, it is well suited for uncovering how individuals understand central psychological constructs and how these constructs vary between individuals (Aeschbach et al., 2025).

Experience with Art: Participants were asked about their experience with visual art ("How many years of experience with visual art do you have?"). We clarified that by experience we referred to practical engagement in visual art (e.g., drawing or painting), as well as possible formal studies in visual art.

Art Passion: Participants were asked about their passion in visual art ("In your opinion, how passionate are you about visual art?"). Scores are reported on a Likert type scale, ranging from 1 – Not at all to 10 – Very passionate. This construct was included as a contextual covariate rather than a primary construct of interest, as passion represents a psychologically meaningful individual difference variable reflecting the engagement, commitment, and effort individuals place toward activities they consider important (Sigmundsson et al., 2020; Vallerand et al., 2003). For this purpose, a single-item measure was considered sufficient.

Art Classification: Participants were asked whether or not AI is capable of creating art ("Do you believe artificial intelligence can create art?"). The response was dichotomous, with possible answers "Yes" or "No."

Attitudes Towards AI: Participants filled in the Artificial Intelligence Attitude Scale (AIAS-4; Grassini, 2023), which measures the general attitudes and perception on artificial intelligence technologies. The AIAS-4 consists of 4 items ("I believe that AI will improve my life."), measured on a 10-point Likert scale, where 1 – Not at all and 10 – Completely agree. For this instrument, a Cronbach's alpha of 0.90 was obtained.

2.3. Preliminary data processing

Analyses were conducted using the R Statistical language on Windows 10 x64 (build 19045). To prepare the data for analysis, we followed the guidelines provided by Mayring (2021) regarding standardization and reducing the text to its core meaning. Firstly, words were translated from Romanian to English, using the *polyglotr* R package. After the automatic translation, all words and sentences were analyzed manually by the researchers to ensure the translations are accurate. Where discrepancies between the original word and its supposed translation were found, they were corrected. Additionally, longer sentences were reduced to their core meaning (for example, "easy to see the difference between AI and human" was reduced to "easy to differentiate", while "plagiarism of other styles" was reduced to

"plagiarized"). All instances of negation were reduced to their one-word form (for example "lack of emotion" was reduced to "emotionless"). If the phrases could not be reduced to a single word, the negation was placed in front of them (for example, "devoid of authenticity" became "no authenticity"). Lastly, plural forms were made singular instead (for example, "colors" became "color", while "emotions" became "emotion").

Secondly, given the nature of our data, exploratory analyses besides simple frequency would have reduced interpretability. To convert our qualitative responses into a format that is suitable for statistical analyses, we used the word embedding technique. Word embedding is a method commonly used in Natural Language Processing (NLP; Li & Yang, 2018), and consists of a conversion from qualitative data (words) to quantitative data (numerical data). The result of this conversion is a vector containing 300 different coordinates. This multidimensionality allows for words to retain their meaning, as well as their contextual relationship to each other. For example, the word "king" will have similar coordinates to the word "queen", given their common context. Similarly, the word "man" will have similar values to "king", while "women" to "queen". Word embeddings can be created from scratch, but pretrained models are widely available. Two well-known examples are Word2Vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014, pp. 1532–1543). In this study, we used GloVe model 6B.300d to encode the participant responses. Words and sentences not found in the GloVe vocabulary were excluded from the analysis.

Word embeddings have previously been used to quantify psychologically rich constructs such as emotions (Plisiecki & Sobieszek, 2024), gender stereotypes (Garg et al., 2018) and cultural biases (Durrheim et al., 2023), offering a way to uncover latent semantic structures in individuals' attitudes and conceptual associations towards a topic, without requiring explicit self-report. In a sense, word embeddings are not simply statistical representations, but psychologically plausible proxies of participants' mental semantic networks (Grand et al., 2022; Kozłowski et al., 2019; Kumar, 2021), which make them a valuable tool in modeling participants' mental representation of different kinds of art in particular.

2.4. Data preparation

Due to high dimensionality of the embeddings, as a first step in our analyses, we used Principal Component Analysis (PCA). PCA is a dimensionality reduction technique, which allows us to reduce the numbers of dimensions while preserving most of the variance (Greenacre et al., 2022; Jolliffe & Cadima, 2016). The analysis was conducted using the *prcomp* R function, from the *stats* package.

In order to determine the number of principal components to keep, we initially followed the guidelines proposed by Jolliffe (2002), keeping all components with eigenvalues greater than 1 (the Kaiser criterion). This approach was chosen over parallel analysis, which is commonly used for latent construct identification in EFA analysis, because variance-explained thresholds are an widely used for compressing high-dimensional embeddings for downstream analyses, rather than to identify latent psychological constructs (Raunak, 2017; Raunak et al., 2019). This method yielded 65 principal components, explaining 80.7% of the total variance. However, to simplify the model and reduce overfitting, we opted to keep the number of components explaining approximately 70% of the variance. This resulted in the retention of 41 principal components, explaining 70.3% of the variance. Eigenvalues, individual variance explained, and cumulative variance for each principal component are presented in Table 2.

3. Results

3.1. Preliminary data analyses

Firstly, we conducted correlation analyses on Experience with Art,

Table 2
Eigenvalues, individual variance, cumulative variance and percentual cumulative variance explained for the first 41 components.

Component	Eigenvalue	Individual variance	Cumulative variance	Percentual cumulative variance
1	24.442	0.0815	0.0815	8.2%
2	15.884	0.0529	0.1344	13.4%
3	13.858	0.0462	0.1806	18.1%
4	12.858	0.0429	0.2235	22.3%
5	11.912	0.0397	0.2632	26.3%
6	9.199	0.0307	0.2938	29.4%
7	8.826	0.0294	0.3233	32.3%
8	7.372	0.0246	0.3478	34.8%
9	7.105	0.0237	0.3715	37.1%
10	6.344	0.0211	0.3927	39.3%
11	5.948	0.0198	0.4125	41.3%
12	5.329	0.0178	0.4303	43.0%
13	4.790	0.0160	0.4462	44.6%
14	4.526	0.0151	0.4613	46.1%
15	4.318	0.0144	0.4757	47.6%
16	4.206	0.0140	0.4897	49.0%
17	4.066	0.0136	0.5033	50.3%
18	3.611	0.0120	0.5153	51.5%
19	3.496	0.0117	0.5270	52.7%
20	3.303	0.0110	0.5380	53.8%
21	3.228	0.0108	0.5487	54.9%
22	3.138	0.0105	0.5592	55.9%
23	3.121	0.0104	0.5696	57.0%
24	2.947	0.0098	0.5794	57.9%
25	2.825	0.0094	0.5888	58.9%
26	2.723	0.0091	0.5979	59.8%
27	2.629	0.0088	0.6067	60.7%
28	2.560	0.0085	0.6152	61.5%
29	2.432	0.0081	0.6233	62.3%
30	2.376	0.0079	0.6312	63.1%
31	2.304	0.0077	0.6389	63.9%
32	2.172	0.0072	0.6462	64.6%
33	2.148	0.0072	0.6533	65.3%
34	2.051	0.0068	0.6602	66.0%
35	1.975	0.0066	0.6667	66.7%
36	1.956	0.0065	0.6733	67.3%
37	1.867	0.0062	0.6795	67.9%
38	1.848	0.0062	0.6857	68.6%
39	1.820	0.0061	0.6917	69.2%
40	1.808	0.0060	0.6977	69.8%
41	1.731	0.0058	0.7035	70.3%

Art Passion and Attitudes Towards AI, to examine whether any atypical relationship between these variables could influence subsequent analyses. As these measures are not normally distributed as measured by the Shapiro-Wilk normality test (Experience with Art: $W = 0.57, p < .001$; Art Passion: $W = 0.97, p < .001$; Attitudes Towards AI: $W = 0.98, p < .001$), we used Spearman correlations. The results indicated a significant positive correlation between Experience with Art and Art Passion, $r = 0.44, 95\% \text{ CI } [0.36, 0.50], p < .001$, and between Art Passion and Attitudes Towards AI, $r = 0.14, 95\% \text{ CI } [0.05, 0.22], p = .003$.

Secondly, we conducted a logistic regression to examine whether Experience with Art, Art Passion, and Attitudes towards AI predicted participants' likelihood of believing that AI can create art. The outcome variable (Art Classification) was binary (0 = "No", 1 = "Yes"), with "No" as the reference category. The model was significant, $\chi^2(3) = 73.95, p < .001$, indicating that the predictors together reliably distinguished participants who believed AI can create art from those who did not. Art Passion negatively predicted Art Classification ($B = -0.14, SE = 0.044, z = -3.10, p = .002, OR = 0.87, 95\% \text{ CI } [0.80, 0.95]$), meaning that for each unit increase in Art Passion, the odds of believing AI can create art were 13% lower. Attitudes Towards AI positively predicted it ($B = 0.37, SE = 0.049, z = 7.55, p < .001, OR = 1.45, 95\% \text{ CI } [1.32, 1.60]$), meaning that for each unit increase in positive AI attitudes, the odds of believing AI can create art were 45% higher. Experience with Art was not a significant predictor ($B = -0.018, SE = 0.025, z = -0.69, p = .49,$

$OR = 0.98, 95\% \text{ CI } [0.93, 1.03]$). The intercept was significant ($B = -1.27, SE = 0.35, z = -3.61, p < .001, OR = 0.33, 95\% \text{ CI } [0.14, 0.55]$). The model showed improved fit over the null model (residual deviance = 695.04, null deviance = 768.99, AIC = 703.04).

3.2. Cluster analysis

To examine the semantic structure of words used to describe traditional visual art and AI art, we performed k-means clustering (Ikotun et al., 2023; Y. Ma et al., 2024) on the first 41 principal component scores from the word embeddings, separately for AI art words and traditional visual art words. For both categories of words, the analysis was run for 5 clusters ($k = 5$); this number was chosen by visual inspection of the elbow plot, which indicates diminishing returns in within-cluster sum of squares (WSS) after 5 clusters. Given that WSS usually continues to decrease the more clusters are included in the analysis (Jain, 2010), we decided to settle for 5 clusters in order to balance psychological interpretability and statistical separation in this high-dimensional space.

Next, we calculated the K-means on the word embedding data. The algorithm was run with 100 random starts and, including duplicates, cluster sizes ranged from 84 to 338 words for the AI art category, and from 91 to 472 words for the traditional visual art category. Cluster quality was analyzed using the silhouette coefficient. The average silhouette width coefficient for traditional visual art words is 0.31 (range between -0.2 and 0.96), while for AI art words the coefficient is 0.15 (range between -0.17 and 0.88). These coefficients suggest that for traditional visual art, clusters are moderately separated, while for AI art, they are less distinct (Batool & Hennig, 2021; Rousseeuw, 1987). However, given the high dimensionality of the data and the conceptual interpretability of the clusters, we judge the small coefficient of the AI arts words to be acceptable (Shirkhorshidi et al., 2014).

Fig. 1 displays the most frequent words in each cluster, for each type of art. For traditional visual art, the clusters are "Emotion and Expressiveness", "Creative Process", "Aesthetic Beauty", "Color", and "Art Forms and Styles", while for AI art the clusters are "Technological Innovation", "Artificial and Robotic", "Lack of Emotion and Authenticity", "Fake and Stolen", and "Novel and Abstract".

3.3. General centroids

To test the overall semantic separation between words used to describe traditional visual art and AI art, we calculated the Euclidean distance between the traditional visual art centroid and the AI art centroid in the 41-dimensional PCA space, which was 6.30. This indicates a substantial semantic distinction between the vocabularies used for each art form. A Hotelling's T-squared test was conducted to compare the overall centroids of words used to describe traditional visual art and AI art. The analysis revealed a significant difference between the two groups' centroids ($T^2 = 77.26, df_1 = 41, df_2 = 2988, p < .001$).

3.4. Cluster centroids

To test the semantic separation between clusters, a MANOVA analysis was conducted for both traditional visual art and AI art words to determine whether their respective 5 clusters were statistically distinct from each other. For the traditional visual art clusters, the analysis revealed a significant effect of cluster membership on the 41 PCA components, $F(164,6164) = 331.38, \text{ Pillai's Trace} = 3.59, p < .001$, indicating that the semantic themes captured by these clusters are indeed significantly different from one another. Similarly, for the AI art clusters, the MANOVA yielded a significant effect of cluster membership, $F(164, 5620) = 163.06, \text{ Pillai's Trace} = 3.31, p < .001$, which confirms that its five thematic clusters are also semantically distinct from one another.

To further examine differences between clusters, we conducted pairwise comparisons using a permutation-based Mahalanobis distance

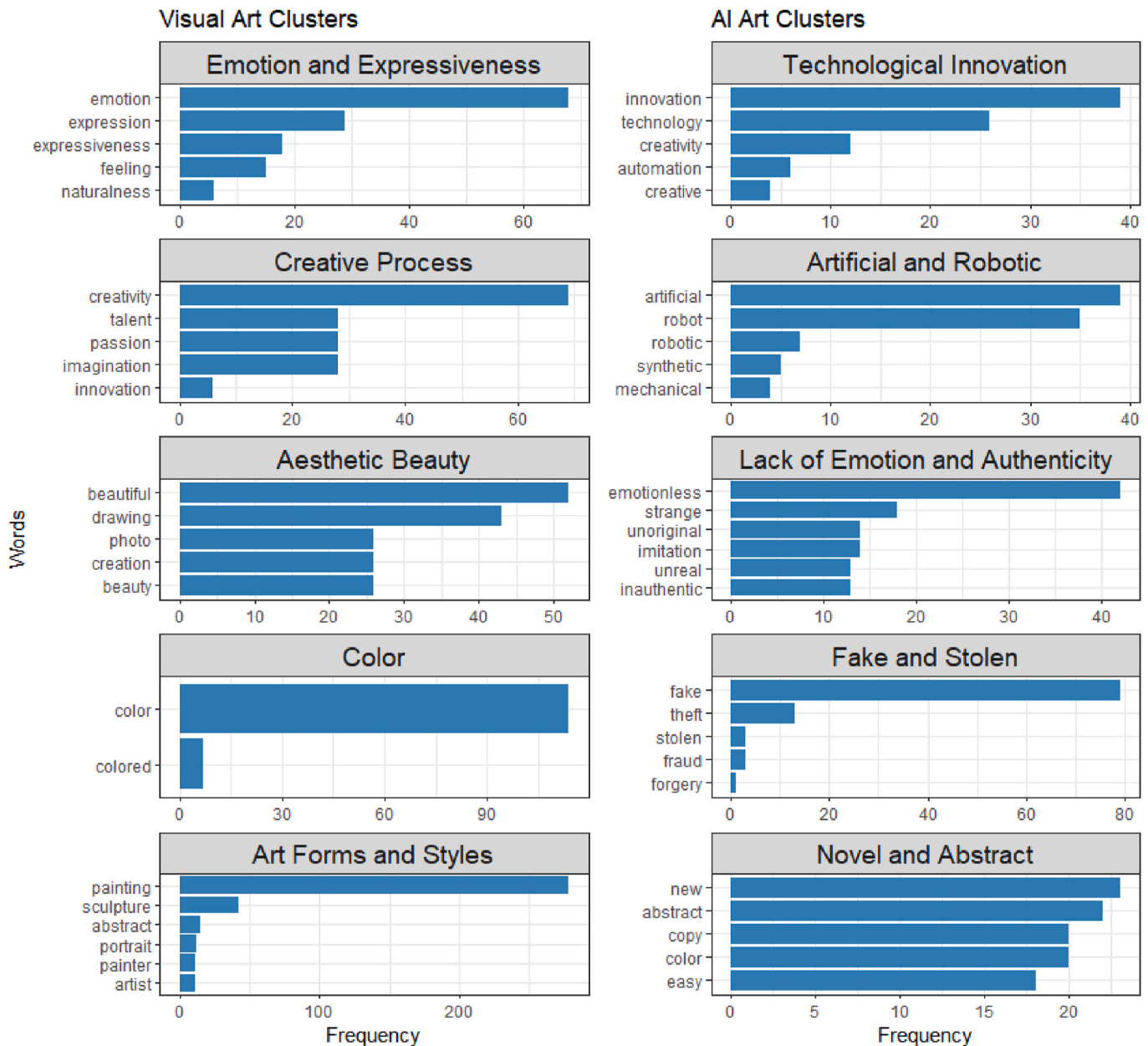


Fig. 1. The most prevalent words for each cluster, for traditional visual art and AI art.

test (5000 permutations), separately for AI art and traditional visual art clusters. Smaller Mahalanobis distances indicate proximity to cluster centroids, whereas larger distances suggest outliers. This approach was preferred over Hotelling's T^2 , which can fail in high-dimensional or highly collinear data due to covariance matrix singularity. Given the strong intercorrelations across embedding components, the Mahalanobis distance test with a Moore-Penrose pseudoinverse and permutation-based significance testing provided a more robust alternative. All cluster pairs differed significantly for both traditional visual art and AI art clusters (Table 3), indicating that the categories were distinct.

3.5. Predicting word choice based on attitudes towards AI

To investigate whether individual differences in attitudes towards AI (AIAS-4) influenced the words used to describe traditional visual art and AI art, two separate MANOVAs were conducted. The AIAS-4 total score was used to predict the proportion of words participants used that fell into each of the five clusters, separately for the two categories of art.

For traditional visual art, the overall multivariate test revealed that AIAS-4 did have a statistically significant effect on the patterns of words they used across the various clusters, $F(5, 554) = 2.22$, Pillai's Trace = 0.019, $p = .05$. Following this overall test, individual univariate regressions were conducted to examine specific cluster proportions predicted by AIAS-4. Results indicated that AIAS-4 was a statistically significant negative predictor of words in the Emotion and Expressiveness cluster ($b = -0.01$, $t = -2.237$, $p = .03$). This suggests that higher scores on the AIAS-4 tended to be associated with lower proportion of words that fall within the Emotion and Expressiveness cluster when describing traditional visual art. Additionally, AIAS-4 was a statistically significant negative predictor of words in the Creative Process cluster ($b = -0.01$, $t = -1.93$, $p = .05$). This shows that when describing traditional visual art, higher AIAS-4 scores tend to be associated with lower proportion of words that fall into the Creative Process cluster. Lastly, the AIAS-4 score did not significantly predict word proportions in the Color ($b = -0.00$, $t = -0.05$, $p = .96$), Art Forms and Styles ($b = 0.01$, $t = 1.22$, $p = .22$), or Aesthetic Beauty ($b = 0.003$, $t = 0.58$, $p = .56$) clusters.

Table 3

Pairwise Mahalanobis distance comparisons between clusters for traditional visual art and AI art words.

Category	Cluster 1	Cluster 2	Mahalanobis Distance	p
Traditional Visual Art	Aesthetic Beauty	Emotion and Expressiveness	2.4492	<0.001
	Aesthetic Beauty	Creative Process	2.4154	<0.001
	Aesthetic Beauty	Color	2.7931	<0.001
	Aesthetic Beauty	Art Forms and Styles	2.0445	<0.001
	Emotion and Expressiveness	Creative Process	2.0042	<0.001
	Emotion and Expressiveness	Color	2.0086	<0.001
	Emotion and Expressiveness	Art Forms and Styles	2.2285	<0.001
	Creative Process	Color	2.0351	<0.001
	Creative Process	Art Forms and Styles	2.1527	<0.001
	Color	Art Forms and Styles	2.3516	<0.001
AI Art	Technological Innovation	Lack of Emotion and Authenticity	2.1624	<0.001
	Technological Innovation	Artificial and Robotic	2.1923	<0.001
	Technological Innovation	Fake and Stolen	2.0415	<0.001
	Technological Innovation	Novel and Abstract	2.0158	<0.001
	Lack of Emotion and Authenticity	Artificial and Robotic	1.9965	<0.001
	Lack of Emotion and Authenticity	Fake and Stolen	2.8262	<0.001
	Lack of Emotion and Authenticity	Novel and Abstract	2.4836	<0.001
	Artificial and Robotic	Fake and Stolen	2.8526	<0.001
	Artificial and Robotic	Novel and Abstract	2.5652	<0.001
	Robotic	Novel and Abstract	1.8340	<0.001
	Fake and Stolen	Novel and Abstract		

For AI art, the overall multivariate test revealed that AIAS-4 had a statistically significant effect on the combined set of AI art words cluster proportions, $F_{(5, 541)} = 6.66$, Pillai's Trace = 0.058, $p < .001$. Following this test, the results of each individual univariate regression indicated that AIAS-4 was a statistically significant positive predictor of words in the Technological Innovation ($b = 0.017$, $t = 2.87$, $p = .004$) and Novel and Abstract ($b = 0.017$, $t = 2.66$, $p = .008$) clusters. This suggests that higher AIAS-4 scores tended to be associated with a higher proportion of words categorized within the Technological Innovation and Novel and Abstract clusters when describing AI art. In addition, AIAS-4 was a statistically significant negative predictor of words in the Fake and Stolen ($b = -0.01$, $t = -3.82$, $p < .001$) and Lack of Emotion and Authenticity ($b = -0.02$, $t = -3.99$, $p < .001$) clusters. This indicates that higher AIAS-4 scores were associated with a lower proportion of words falling into the Lack of Emotion and Authenticity and Fake and Stolen clusters. Lastly, the AIAS-4 total score did not significantly predict word proportions in the Artificial and Robotic cluster ($b = -0.00$, $t = -1.20$, $p = .23$).

4. Discussion

The core objective of this exploratory study was to investigate the underlying structure of cognitive schemas related to traditional visual art and AI-generated art, and whether these schemas are distinct enough to explain the negative aesthetic bias against AI art, especially when the author is known to be non-human (Brauner et al., 2023; Chiarella et al., 2022; Hong, 2018). Psychologically, these descriptions reflect an underlying cognitive framework in which aesthetic evaluation of visual art

is intertwined with emotional and evaluative processes: people tend to value artworks that evoke feelings, demonstrate creativity, and appear authentic, whereas AI-generated artworks are often assessed through a lens that emphasizes technological advancement and questions of originality.

Our cluster analysis on word embeddings revealed five clusters for both traditional visual art and AI art. The emergent clusters for traditional visual art are "Emotion and Expressiveness", "Creative Process", "Aesthetic Beauty", "Color", and "Art Forms and Styles", while for AI art the clusters are "Technological Innovation", "Artificial and Robotic", "Lack of Emotion and Authenticity", "Fake and Stolen", and "Novel and Abstract".

The clusters reveal that cognitive schemas of traditional visual art encapsulate both evaluative and descriptive dimensions. First, participants emphasized the emotional impact of traditional visual art, highlighted by words such as "emotion", "expressiveness", and "feeling", the creative process, characterized by words such as "creativity", "talent", and "imagination", and its aesthetic properties, described by words such as "beautiful", and "beauty". The research literature has already shown that positive emotionality and aesthetic beauty are strongly related when appraising art (Chuan-Peng et al., 2020; Miller et al., 2025; Vartanian, 2022), and our results support these findings. In the "Aesthetic Beauty" cluster we also observed "drawing" and "photo", which are two of the most dominant traditional visual art mediums (Rodríguez Novo et al., 2021). We argue that these words function as prototypes that guide the individual's mental representation of aesthetically beautiful traditional visual art. Second, participants describe traditional visual art in terms of color and traditional art forms. The "Color" cluster consists of two words, "color" and "colored", which represents a fundamental visual element in art perception (Palmer et al., 2013). The "Color" cluster highlights the importance of chromatic information especially in modulating emotional valence (Song et al., 2025) and aesthetic preference (Albers et al., 2020). Similarly, the "Art Forms and Styles" cluster encompasses words describing specific art modalities or styles, such as "painting", "sculpture", or "portrait". This suggests that people conceptualize visual art not only as images, but as physical art forms as well, which cannot be easily replicated by AI. Past research shows that the physical context and medium affects aesthetic experience (Szubielska et al., 2021), especially in terms of interest, surprise or confusion (Reymond et al., 2020).

For AI art, the cluster analysis reveals a more diverse cognitive schema, consisting of concepts related to its technical nature, as well as aspects that contrast with elements of the traditional visual art schema. To describe its technical nature, participants used terms such as "innovation", "technology", and "automation". This might imply that people recognize the usefulness and applicability of AI in general, while still being skeptical about its capabilities to create visual art. This skepticism may stem from broader fears regarding the potential consequences of AI development (Kitchens & Meier, 2025). Accompanying these words are the words "creativity" and "creative", which might suggest that this cluster shares some conceptual similarities with the "Creative Process" cluster of traditional visual art. However, rather than implying intentional creativity, this pattern suggests that participants perceive AI as capable of producing art-like objects (Tigre Moura et al., 2023). The "Novel and Abstract" cluster complements this idea, because AI is such a new concept for many, and is seen as "new" and "abstract". This idea is further supported by the positive relationship between participants' passion for visual art and their general attitudes toward AI. It suggests that individuals more passionate about visual art may appreciate AI as a novel technique, yet remain divided on whether its outputs constitute genuine art, as the likelihood of considering AI capable of creating art decreased with greater passion for art. Additionally, despite being innovative, AI art is also seen as "artificial", "robotic", and "synthetic" on one hand, and "fake" and "stolen" on the other. Another important dimension is that of emotionality. AI art has been described as "emotionless", "strange", and "unoriginal". Samo and Highhouse (2023)

suggest that one important aesthetic judgment factor that differentiates human-made art from machine-generated art is positive emotionality. Our findings support this idea, given that “emotion” characterizes a traditional visual art cluster, while “emotionless” characterizes an AI art cluster. These words suggest that human-made art is defined by its capability to evoke emotion and express them through said art, while AI-made art is defined by a lack of emotions and inability to genuinely express emotion.

We also note that for traditional visual art, the “Emotion and Expressiveness”, “Creative Process”, and “Aesthetic Beauty” carry positive connotations, whereas the “Color” and “Art Forms and Styles” are more neutral. This suggests that traditional visual art is seen predominantly as positive. However, for AI art, we observed a more polarized semantic structure, with “Technological Innovation” and “Novel and Abstract” clusters being positive, while “Artificial and Robotic”, “Lack of Emotion and Authenticity”, and “Fake and Stolen” clusters being negative. This suggests that AI art is not seen as entirely positive or negative, but more ambivalent. Traditional visual art seems to elicit a more predictable positive appraisal, likely because it aligns with established schemas of what “art” is and carries affective and aesthetic associations. In contrast, the coexistence of positive and negative clusters for AI art may reflect a conflict between cognitive appraisal and affective reaction. People recognize AI art as novel and creative, while simultaneously questioning its authenticity and emotional value. This suggests that AI art challenges traditional mental representations of art, engaging both evaluative and moral-emotional processes and leading to ambivalence. Prior research indicates that ambivalence is psychologically uncomfortable and often motivates individuals to resolve it by leaning one way in their judgement, resulting in biased processing (Nordgren et al., 2006; van Harreveld et al., 2009). This biased processing might be accentuated because traditional visual art is consistently evaluated positively, in direct comparison to AI art (Neef et al., 2024).

Previous research emphasizes that people who hold the belief that AI is unable to create art rated computer-generated artworks lower overall for composition, degree of expression and aesthetic value (Hong & Curran, 2019). However, when it is unclear whether the artworks are created by humans or AI, and no clear explicit bias towards AI artworks is shown, an implicit bias was observed, consisting of a longer time spent viewing the artwork if it is thought to be made by a human (Zhou & Kawabata, 2023).

Our results suggest that individuals with positive attitudes toward artificial intelligence describe traditional visual art and AI art differently than those with negative attitudes. When describing traditional visual art, those with more positive attitudes towards AI used fewer words related to emotion, expressiveness, and creative processes. When describing AI art, they used more words related to technological innovation and novelty, while using fewer words suggesting the AI art is fake, stolen, or lacking emotion and authenticity.

In conclusion, our exploratory analysis provides a foundation for better understanding what differentiates AI art from traditional visual art. We identified the key components underlying people's evaluations of each art type and the concepts associated with thinking about traditional visual art and AI art.

4.1. Limitations and future directions

This study has several limitations. Although the free association method revealed complex relationships between words, it may have captured only the most salient or easily verbalized aspects of the phenomenon rather than a complete picture. The qualitative nature of the data also makes quantification challenging without some loss of meaning. While we addressed this using word embeddings, some nuances may still have been lost because the corpus included only single words.

Secondly, the relatively low silhouette coefficient for the AI art clusters suggests that the cognitive schema for AI art is more ambiguous or less clearly defined than for traditional art. This might be due to

participants often providing words related to AI in general rather than to AI art specifically. This highlights that in people's minds, the cognitive schema for AI art is defined more by its “AI” component, and not its “art” component.

Additionally, participants were recruited using the snowball sampling technique, which may have introduced sampling bias, as this method tends to produce samples that are socially interconnected and may not be representative of the broader population (Tripathy et al., 2026). This is reflected in the demographic composition of our sample, which was predominantly female, urban, and consisted largely of university students. Future studies should aim to recruit more diverse and representative samples.

Furthermore, the cross-sectional design of this study limits the conclusions that can be drawn about the stability of the identified cognitive schemas over time. As data were collected at a single point in time, it is unclear whether the semantic distinctions between traditional visual art and AI art reflect stable mental representations or transient attitudes shaped by the current cultural moment (Bergdahl et al., 2023). Longitudinal designs would allow researchers to track how these cognitive schemas evolve as AI art becomes more prevalent in everyday life.

A further limitation of this study is the absence of a pre-registration. Given the exploratory nature of this research, the data analysis decisions were made as the study progressed, which could decrease the reproducibility of the findings. We acknowledge that pre-registration has become an important aspect of psychological research in response to the replication crisis (Nosek et al., 2018), and we encourage future replications of this work to be pre-registered in order to clearly distinguish between confirmatory and exploratory analyses.

Regarding future research directions, replicating this study in other languages and cultures would be valuable. Our research was conducted in Romania, so its results are primarily representative of this country and its neighboring countries. In countries where visual art plays a larger role in everyday life, individuals might hold different cognitive schemas about art and AI. For example, Nordic countries have been observed to show the highest levels of engagement with the arts compared to Eastern or Southern Europe (Purhonen et al., 2023). In this regard, a particularly interesting future direction would be to replicate this study in Southern European countries and compare the resulting cognitive schemas with those obtained in Eastern Europe, where cultural attitudes toward both traditional art and emerging technologies may differ substantially (Darda & Cross, 2022).

Additionally, since people often think about visual art in terms of the emotions it evokes, we recommend conducting a sentiment analysis to explore how they actually feel about traditional visual art and AI art. Using richer descriptions rather than single words could provide additional context for understanding ambivalent cognitive schemas toward AI art, as negative aspects may be complemented by positive ones overlooked in single-word responses.

Lastly, this approach of examining underlying cognitive schemas could be complemented by an experimental design in which participants are prompted to provide the words that come to mind while viewing an image presented as either human-made or AI-made. This design could provide deeper insight into how contextual information shapes people's judgments of visual art, and clarify the importance of contextual cues compared to purely perceptual features.

4.2. Theoretical and practical implications

From a theoretical perspective, this study expands the current understanding of the definition of art and supports the importance of prior attitudes in judging it. Given the rapidly expanding prevalence of AI in day-to-day domains (Islam et al., 2022), our research highlights that people hold different preconceived notions about what constitutes traditional visual art versus AI art. This challenges traditional models of aesthetic judgement, such as the processing fluency theory (Reber et al., 2004), the pleasure-interest model (Graf & Landwehr, 2017) and the

information processing framework (Leder et al., 2004), which primarily focus on the perceptual interaction between viewer and artwork, without considering how judgments may change depending on how the author is perceived (Darewych, 2023; Di Dio et al., 2023). This helps better understand the aesthetic negative bias that AI art often receives (Chiarella et al., 2022), which might be explained, on one hand, by how the AI art is implicitly considered to be fake, stolen emotionless and inauthentic, while the technology itself is seen as novel and creative. On the other hand, this bias might be explained by how people think more positively of traditional visual art when directly comparing it to AI art (Neef et al., 2024), suggesting a double processing route for aesthetic evaluation.

From a practical perspective, our results offer useful directions for both the development of generative AI algorithms and the practices of cultural institutions. Since AI-generated art is often evaluated more negatively, developers could emphasize features that make the process appear more collaborative, such as highlighting human–AI co-creation (Jordanous, 2017, pp. 159–166), more intentional, by communicating the rationale or purpose behind the generated artworks (Jucker et al., 2014), or more emotionally expressive, by embedding stylistic cues that convey affect (L. Ma et al., 2024). At the same time, our findings can serve as a resource for museums, galleries, and curators, who increasingly face the challenge of exhibiting AI art alongside traditional works (Maksimova, 2025). Clear communication about how AI artworks are made and the degree of implication of a human artist could help viewers appraise these works within an established artistic framework, which is independent from that of traditional visual art.

In addition to these implications, the present findings are also relevant for clinical contexts in which visual art is used as a therapeutic medium. While traditional visual art is cognitively associated with emotionality, expressiveness, and authenticity, AI-generated art activates more ambivalent schemas related to artificiality and lack of emotion, which may differentially affect clients' engagement, emotional resonance, and sense of agency. Our results suggest that therapists should not assume psychological equivalence between human-made and AI-generated art, but instead consider how clients' pre-existing attitudes toward AI may shape their responses to art-based interventions.

For example, for patients with schizophrenia, who often exhibit fragmented identity, disorganized thinking, and difficulties identifying and expressing emotional states, art therapy has been shown to be particularly valuable precisely because it facilitates emotional engagement and self-expression when verbal interaction is difficult (Barrett et al., 2022; Du et al., 2024). However, the ambivalent schema associated with AI art, characterized by perceptions of artificiality, inauthenticity, and lack of emotion, may undermine these therapeutic goals by activating cognitive dissonance at a time when coherence and emotional grounding are central to treatment. In contrast, for patients with dementia, for whom cognitive stimulation and novel sensory experiences are primary therapeutic objectives, AI art's association with novelty and technological innovation may offer a more compatible stimulus (Masika et al., 2020; Zhao et al., 2025). As such, therapists should be cautious to the potential confusion that ambivalent or artificial imagery may provoke in patients with impaired ability to distinguish internal from external experiences.

More broadly, our findings suggest that individual attitudes toward AI constitute a potentially meaningful aspect to be considered in therapeutic contexts, as patients with more positive attitudes toward AI were associated with reduced use of negative descriptors and greater engagement with innovation-related concepts. Therapists are therefore encouraged to assess patients' pre-existing attitudes toward artificial intelligence prior to incorporating AI-generated visual material into sessions, in order to anticipate potential emotional and cognitive responses and tailor their approach accordingly. As Zubala et al. (2025) caution, the introduction of AI art in psychotherapy risks undermining client agency if not carefully managed, and the present findings provide a starting point for understanding why this risk may vary substantially

across clinical populations. Based on these considerations, we outline a set of practical recommendations for the use of AI-generated visual material in psychotherapeutic and art-therapeutic settings (see Table 4).

5. Conclusion

The present exploratory study investigated how cognitive schemas shape perceptions of traditional visual art and AI art, and how attitudes toward AI influence these perceptions. Using semantic clustering of word embeddings from free associations, we identified five distinct clusters for each art type. Traditional visual art centered on emotion and expressiveness, creative processes, aesthetic beauty, color, and art forms and styles, whereas AI art centered on technological innovation, artificial and robotic qualities, lack of emotion and authenticity, fake and stolen content, and novelty and abstraction.

These differences indicate that people conceptualize traditional and AI art differently. Traditional art schemas were predominantly positive, whereas AI art schemas were more ambivalent, combining positive technological aspects with concerns about authenticity. This ambivalence may help explain the documented negative bias against AI art when authorship is disclosed.

Furthermore, individual differences in attitudes toward AI predicted the words used to describe both art types. More positive attitudes were associated with fewer emotion-related words for traditional art and more innovation-related words for AI art, highlighting the role of top-down schemas in aesthetic evaluation beyond perceptual attributes alone. These findings suggest that models of aesthetic appreciation

Table 4
Practical recommendations for the use of AI-generated visual material in art-based psychotherapy.

Recommendation	Description
Assess clients' attitudes toward AI prior to intervention	Before introducing AI-generated visual material, therapists should explore clients' beliefs and attitudes toward artificial intelligence, as these attitudes may influence emotional engagement, perceived authenticity, and openness to the therapeutic process.
Avoid assuming equivalence between AI-generated and human-made art	AI-generated art should not be treated as psychologically equivalent to traditional visual art, as clients may associate it with artificiality, lack of emotion, or ethical concerns, potentially limiting its therapeutic impact.
Emphasize client agency and human intentionality	When AI tools are used, therapists should foreground the client's role in decision-making (e.g., prompt creation, selection, interpretation), framing the process as collaborative human–AI co-creation rather than autonomous machine production.
Use explicit therapeutic framing when introducing AI imagery	Clear explanation of why AI-generated images are used, how they are created, and how they relate to therapeutic goals may help reduce skepticism and prevent negative schemas related to inauthenticity or emotional detachment.
Monitor emotional resonance and meaning-making processes	Therapists should actively monitor whether AI-generated imagery facilitates or inhibits emotional expression, symbolic meaning, and personal relevance, adjusting the intervention if the material elicits disengagement or discomfort.
Be attentive to ethical and authenticity-related concerns	Given associations of AI art with “fake” or “stolen” content, therapists should be prepared to address ethical questions transparently, especially when such concerns interfere with trust or therapeutic alliance.

should incorporate authorship schemas and technological attitudes as meaningful moderators. Overall, traditional and AI art engage different cognitive schemas, providing a psychological basis for persistent aesthetic skepticism toward AI art despite its visual similarity to human works. As AI continues to integrate into creative domains, addressing these underlying cognitive structures will be essential for informed discussions about the future of art.

CRediT authorship contribution statement

Alexandru Popescu: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Andreea Huțul:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tudor-Daniel Huțul:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Andrei Corneliu Holman:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Ethics statement

This study's protocol was designed following the ethical requirements specific to the Faculty of Psychology and Education Sciences, Alexandru Ioan Cuza University of Iași, Romania, before beginning the study (supervised by Alexandru Popescu). All participants voluntarily participated in the study and gave written informed consent following the Declaration of Helsinki and the national laws from Romania regarding ethical conduct in scientific research, technological development, and innovation. No animal studies are presented in this manuscript.

Ethical approval

The study was approved by the Ethics Committee of the Faculty of Psychology and Education Sciences, Alexandru Ioan Cuza University of Iași, Romania, before beginning the study and supervised by Alexandru Popescu (No. 1636/18.09.2025).

Funding

The authors received no financial support for the research authorship and/or publication of this article.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper. The authors also declare no financial interests/personal relationships, which may be considered as potential competing interests.

Data availability

Research Link Provided.

<https://osf.io/rhk8f/overview> (OSF:)

References

- Aeschbach, S., Mata, R., & Wulff, D. U. (2025). Mapping mental representations with free associations: A tutorial using the R package associatoR. *Journal of Cognition*. <https://doi.org/10.5334/joc.407>
- Agudo, U., Arrese, M., Liberal, K. G., & Matute, H. (2022). Assessing emotion and sensitivity of AI artwork. *Frontiers in Psychology*, 13. <https://doi.org/10.3389/fpsyg.2022.879088>
- Agüera y Arcas, B. (2017). Art in the age of machine intelligence. *Arts*, 6(4), Article 4. <https://doi.org/10.3390/arts6040018>
- Albers, A. M., Gegenfurtner, K. R., & Nascimento, S. M. C. (2020). An independent contribution of colour to the aesthetic preference for paintings. *Vision Research*, 177, 109–117. <https://doi.org/10.1016/j.visres.2020.08.005>
- Altenmüller, M. S., & Plewe, M. C. (2024). (Not) alone in the museum: Implicit social influence on art appreciation. *Psychology of Aesthetics, Creativity, and the Arts*, No *Pagination Specified-No Pagination Specified*. <https://doi.org/10.1037/aca0000713>
- Anantrasirichai, N., & Bull, D. (2022). Artificial intelligence in the creative industries: A review. *Artificial Intelligence Review*, 55(1), 589–656. <https://doi.org/10.1007/s10462-021-10039-7>
- Anglada-Tort, M., Steffens, J., & Müllensiefen, D. (2019). Names and titles matter: The impact of linguistic fluency and the affect heuristic on aesthetic and value judgements of music. *Psychology of Aesthetics, Creativity, and the Arts*, 13, 277–292. <https://doi.org/10.1037/aca0000172>
- Aris, S., Aeni, B., & Nosrati, S. (2023). A digital aesthetics? Artificial intelligence and the future of the art. *Journal of Cyberspace Studies*, 7(2), 219–236. <https://doi.org/10.22059/jcss.2023.366256.1097>
- Augustin, M. D., Carbon, C.-C., & Wagemans, J. (2012). Artful terms: A study on aesthetic word usage for visual art versus film and music. *I-Perception*, 3(5), 319–337. <https://doi.org/10.1068/10511aap>
- Augustin, M. D., Wagemans, J., & Carbon, C.-C. (2012). All is beautiful? Generality vs. specificity of word usage in visual aesthetics. *Acta Psychologica*, 139(1), 187–201. <https://doi.org/10.1016/j.actpsy.2011.10.004>
- Bara, I., Ramsey, R., & Cross, E. S. (2025). AI contextual information shapes moral and aesthetic judgments of AI-generated visual art. *Cognition*, 257, Article 106063. <https://doi.org/10.1016/j.cognition.2025.106063>
- Barrett, H., Holtum, S., & Wright, T. (2022). Therapist and client experiences of art therapy in relation to psychosis: A thematic analysis. *International Journal of Art Therapy*, 27(3), 102–111. <https://doi.org/10.1080/17454832.2022.2046620>
- Batool, F., & Hennig, C. (2021). Clustering with the average silhouette width. *Computational Statistics & Data Analysis*, 158, Article 107190. <https://doi.org/10.1016/j.csda.2021.107190>
- Belke, B., Leder, H., Strobach, T., & Carbon, C.-C. (2010). Cognitive fluency: High-level processing dynamics in art appreciation. *Psychology of Aesthetics, Creativity, and the Arts*, 4(4), 214–222. <https://doi.org/10.1037/a0019648>
- Bellaiche, L., Shahi, R., Turpin, M. H., Ragnhildstveit, A., Sprockett, S., Barr, N., Christensen, A., & Seli, P. (2023). Humans versus AI: Whether and why we prefer human-created compared to AI-created artwork. *Cognitive Research: Principles and Implications*, 8(1), 42. <https://doi.org/10.1186/s41235-023-00499-6>
- Bergdahl, J., Latikka, R., Celuch, M., Savolainen, I., Soares Mantere, E., Savela, N., & Oksanen, A. (2023). Self-determination and attitudes toward artificial intelligence: Cross-national and longitudinal perspectives. *Telematics and Informatics*, 82, 102013. <https://doi.org/10.1016/j.tele.2023.102013>
- Berlyne, D. E. (1970). Novelty, complexity, and hedonic value. *Perception & Psychophysics*, 8(5), 279–286. <https://doi.org/10.3758/BF03212593>
- Brauner, P., Hick, A., Philipsen, R., & Ziefle, M. (2023). What does the public think about artificial intelligence?—A criticality map to understand bias in the public perception of AI. *Frontiers of Computer Science*, 5. <https://doi.org/10.3389/fcomp.2023.1113903>
- Brewer, P. R., Cuddy, L., Dawson, W., & Stise, R. (2025). Artists or art thieves? Media use, media messages, and public opinion about artificial intelligence image generators. *AI & Society*, 40(1), 77–87. <https://doi.org/10.1007/s00146-023-01854-3>
- Brieber, D., Nadal, M., & Leder, H. (2015). In the white cube: Museum context enhances the valuation and memory of art. *Acta Psychologica*, 154, 36–42. <https://doi.org/10.1016/j.actpsy.2014.11.004>
- Brinck, I. (2018). Empathy, engagement, entrainment: The interaction dynamics of aesthetic experience. *Cognitive Processing*, 19(2), 201–213. <https://doi.org/10.1007/s10339-017-0805-x>
- Bruder, K. A., & Ucock, O. (2000). Interactive art interpretation: How viewers make sense of paintings in conversation. *Symbolic Interaction*, 23(4), 337–358. <https://doi.org/10.1525/si.2000.23.4.337>
- Brumm, A., Oktaviana, A. A., Burhan, B., Hakim, B., Lebe, R., Zhao, J., Sulistyarto, P. H., Ririmasse, M., Adhityatama, S., Sumantri, I., & Aubert, M. (2021). Oldest cave art found in Sulawesi. *Science Advances*, 7(3). <https://doi.org/10.1126/sciadv.abd4648>. eabd4648.
- Callaway, K., Rowatt, W. C., Al-Kire, R. L., & Schnitker, S. A. (2023). Measuring the (Im) Measurable: On the psycho-socio-spiritual effects of aesthetic experiences of art. *Journal of Psychology & Theology*, 51(3), 352–374. <https://doi.org/10.1177/00916471231158557>
- Chamberlain, R. (2022). The interplay of objective and subjective factors in empirical aesthetics. In B. Ionescu, W. A. Bainbridge, & N. Murray (Eds.), *Human perception of visual information* (pp. 115–132). Springer International Publishing. https://doi.org/10.1007/978-3-030-81465-6_5
- Chamberlain, R., Mullin, C., Scheerlinck, B., & Wagemans, J. (2018). Putting the art in artificial: Aesthetic responses to computer-generated art. *Psychology of Aesthetics, Creativity, and the Arts*, 12(2), 177–192. <https://doi.org/10.1037/aca0000136>

- Chen, X., & Ibrahim, Z. (2023). A comprehensive study of emotional responses in AI-Enhanced interactive installation art. *Sustainability*, 15(22), Article 15830. <https://doi.org/10.3390/su152215830>
- Cheung, M.-C., Law, D., Yip, J., & Wong, C. W. Y. (2019). Emotional responses to visual art and commercial stimuli: Implications for creativity and aesthetics. *Frontiers in Psychology*, 10. <https://doi.org/10.3389/fpsyg.2019.00014>
- Chiarella, S. G., Torromino, G., Gagliardi, D. M., Rossi, D., Babiloni, F., & Cartocci, G. (2022). Investigating the negative bias towards artificial intelligence: Effects of prior assignment of AI-authorship on the aesthetic appreciation of abstract paintings. *Computers in Human Behavior*, 137, Article 107406. <https://doi.org/10.1016/j.chb.2022.107406>
- Choi, S. K., DiPaola, S., Töyrylä, H., DiPaola, S., & Töyrylä, H. (2021). Artistic style meets artificial intelligence. *Journal of Perceptual Imaging*, 4, 1–14. <https://doi.org/10.2352/J.Percept.Imaging.2021.4.2.020501>
- Chuan-Peng, H., Huang, Y., Eickhoff, S. B., Peng, K., & Sui, J. (2020). Seeking the “Beauty Center” in the brain: A meta-analysis of fMRI studies of beautiful human faces and visual art. *Cognitive, Affective, & Behavioral Neuroscience*, 20(6), 1200–1215. <https://doi.org/10.3758/s13415-020-00827-z>
- Coeckelbergh, M. (2017). Can machines create art? *Philosophy & Technology*, 30(3), 285–303. <https://doi.org/10.1007/s13347-016-0231-5>
- Coleman, R. A., & Neimeyer, R. A. (2015). Assessment of subjective client agency in psychotherapy: A review. *Journal of Constructivist Psychology*, 28(1), 1–23. <https://doi.org/10.1080/10720537.2014.939791>
- Cova, F., & Pain, N. (2012). Can folk aesthetics ground aesthetic realism? *The Monist*, 95(2), 241–263. <https://doi.org/10.5840/monist201295214>
- Cupchik, G. C., Vartanian, O., Crawley, A., & Mikulis, D. J. (2009). Viewing artworks: Contributions of cognitive control and perceptual facilitation to aesthetic experience. *Brain and Cognition*, 70(1), 84–91. <https://doi.org/10.1016/j.bandc.2009.01.003>
- Darda, K. M., & Chatterjee, A. (2023). The impact of contextual information on aesthetic engagement of artworks. *Scientific Reports*, 13(1), Article 1. <https://doi.org/10.1038/s41598-023-30768-9>
- Darda, K. M., & Cross, E. S. (2022). The role of expertise and culture in visual art appreciation. *Scientific Reports*, 12, 10666. <https://doi.org/10.1038/s41598-022-14128-7>
- Darewych, T. (2023). The impact of authorship on aesthetic appreciation: A study comparing human and AI-Generated artworks. *Art and Society*, 2(1), 67–73.
- Davies, S. (2015). Defining art and artworks. *The Journal of Aesthetics and Art Criticism*, 73(4), 375–384. <https://doi.org/10.1111/jaac.12222>
- Demmer, T. R., Kühnapfel, C., Fingerhut, J., & Pelowski, M. (2023). Does an emotional connection to art really require a human artist? Emotion and intentionality responses to AI- versus human-created art and impact on aesthetic experience. *Computers in Human Behavior*, 148, Article 107875. <https://doi.org/10.1016/j.chb.2023.107875>
- Di Dio, C., Ardizzi, M., Schieppati, S. V., Massaro, D., Gilli, G., Gallese, V., & Marchetti, A. (2023). Art made by artificial intelligence: The effect of authorship on aesthetic judgments. *Psychology of Aesthetics, Creativity, and the Arts*, No Pagination Specified-No Pagination Specified. <https://doi.org/10.1037/aca0000602>
- Du, S.-C., Li, C.-Y., Lo, Y.-Y., Hu, Y.-H., Hsu, C.-W., Cheng, C.-Y., Chen, T.-T., Hung, P.-H., Lin, P.-Y., & Chen, C.-R. (2024). Effects of Visual Art Therapy on Positive Symptoms, Negative Symptoms, and Emotions in Individuals with Schizophrenia: A Systematic Review and Meta-Analysis. *Healthcare*, 12(11), 1156. <https://doi.org/10.3390/healthcare12111156>
- Durrheim, K., Schuld, M., Mafunda, M., & Mazibuko, S. (2023). Using word embeddings to investigate cultural biases. *British Journal of Social Psychology*, 62(1), 617–629. <https://doi.org/10.1111/bjso.12560>
- Else, J. E., Ellis, J., & Orme, E. (2015). Art expertise modulates the emotional response to modern art, especially abstract: An ERP investigation. *Frontiers in Human Neuroscience*. <https://doi.org/10.3389/fnhum.2015.00525>
- Epstein, Z., Levine, S., Rand, D. G., & Rahwan, I. (2020). Who gets credit for AI-Generated art? *iScience*, 23(9). <https://doi.org/10.1016/j.isci.2020.101515>
- Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, 41(4), 1149–1160. <https://doi.org/10.3758/BRM.41.4.1149>
- Forsythe, A., Nadal, M., Sheehy, N., Cela-Conde, C. J., & Sawey, M. (2011). Predicting beauty: Fractal dimension and visual complexity in art: Predicting beauty in art. *British Journal of Psychology*, 102(1), 49–70. <https://doi.org/10.1348/000712610X498958>
- Fortuna, P., & Modliński, A. (2021). A(D)rtist or counterfeiter? Artificial intelligence as (D)Evaluating factor on the art market. *The Journal of Arts Management, Law, and Society*, 51(3), 188–201. <https://doi.org/10.1080/10632921.2021.1887032>
- Garcia, M. B. (2024). The paradox of artificial creativity: Challenges and opportunities of generative AI artistry. *Creativity Research Journal*, 0(0), 1–14. <https://doi.org/10.1080/10400419.2024.2354622>
- Garg, N., Schiebinger, L., Jurafsky, D., & Zou, J. (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, 115(16), E3635–E3644. <https://doi.org/10.1073/pnas.1720347115>
- Genger, G., & Leder, H. (2015). Titles change the esthetic appreciations of paintings. *Frontiers in Human Neuroscience*, 9. <https://www.frontiersin.org/articles/10.3389/fnhum.2015.00464>
- Genger, G., Leder, H., & Kremer, A. (2014). Context effects on emotional and aesthetic evaluations of artworks and IAPS pictures. *Acta Psychologica*, 151, 174–183. <https://doi.org/10.1016/j.actpsy.2014.06.008>
- Goetz, I., & Carbon, C. C. (2023). The art of experiencing art: On the nature and the origins of the mode of art eXperience (MAX). *Journal of Perceptual Imaging*, 6, 1–19. <https://doi.org/10.2352/J.Percept.Imaging.2023.6.000403>
- Goodfellow, P. (2024). The distributed authorship of art in the age of AI. *Arts*, 13(5), Article 5. <https://doi.org/10.3390/arts13050149>
- Graf, L. K. M., & Landwehr, J. R. (2017). Aesthetic pleasure versus aesthetic interest: The two routes to aesthetic liking. *Frontiers in Psychology*, 8, 15. <https://doi.org/10.3389/fpsyg.2017.00015>
- Grand, G., Blank, I. A., Pereira, F., & Fedorenko, E. (2022). Semantic projection recovers rich human knowledge of multiple object features from word embeddings. *Nature Human Behaviour*, 6(7), 975–987. <https://doi.org/10.1038/s41562-022-01316-8>
- Grassini, S. (2023). Development and validation of the AI attitude scale (AIAS-4): A brief measure of general attitude toward artificial intelligence. *Frontiers in Psychology*, 14. <https://doi.org/10.3389/fpsyg.2023.1191628>
- Greenacre, M., Groenen, P. J. F., Hastie, T., D’Enza, A. I., Markos, A., & Tuzhilina, E. (2022). Principal component analysis. *Nature Reviews Methods Primers*, 2(1), 1–21. <https://doi.org/10.1038/s43586-022-00184-w>
- Grilli, L., & Pedota, M. (2024). Creativity and artificial intelligence: A multilevel perspective. *Creativity and Innovation Management*, 33(2), 234–247. <https://doi.org/10.1111/caim.12580>
- Grüner, S., Specker, E., & Leder, H. (2019). Effects of context and genuineness in the experience of art. *Empirical Studies of the Arts*, 37(2), 138–152. <https://doi.org/10.1177/0276237418822896>
- Grzywacz, N. M., & Aleem, H. (2022). Does amount of information support aesthetic values? *Frontiers in Neuroscience*, 16, Article 805658. <https://doi.org/10.3389/fnins.2022.805658>
- Hassan, A. M., Nelson, J. A., Coert, J. H., Mehrara, B. J., & Selber, J. C. (2023). Exploring the potential of artificial intelligence in surgery: Insights from a conversation with ChatGPT. *Annals of Surgical Oncology*, 30(7), 3875–3878. <https://doi.org/10.1245/s10434-023-13347-0>
- Hattori, E. A., Yamakawa, M., & Miwa, K. (2024). Human bias in evaluating AI product creativity. *Journal of Creativity*, 34(2), Article 100087. <https://doi.org/10.1016/j.jyoc.2024.100087>
- Hayn-Leichsenring, G. U. (2017). The ambiguity of artworks –A guideline for empirical aesthetics research with artworks as stimuli. *Frontiers in Psychology*, 8. <https://doi.org/10.3389/fpsyg.2017.01857>
- Hill, J., Randolph Ford, W., & Farreras, I. G. (2015). Real conversations with artificial intelligence: A comparison between human–human online conversations and human–chatbot conversations. *Computers in Human Behavior*, 49, 245–250. <https://doi.org/10.1016/j.chb.2015.02.026>
- Hong, J.-W. (2018). Bias in perception of art produced by artificial intelligence. In M. Kurosu (Ed.), *Human-computer interaction. Interaction in context* (pp. 290–303). Springer International Publishing. https://doi.org/10.1007/978-3-319-91244-8_24
- Hong, J.-W., & Curran, N. M. (2019). Artificial intelligence, artists, and art: Attitudes toward artwork produced by humans vs. artificial intelligence. *ACM Transactions on Multimedia Computing, Communications, and Applications*, 15(2s). <https://doi.org/10.1145/3326337>, 58:1–58:16.
- Horton, J. C. B., White, M. W., & Iyengar, S. S. (2023). Bias against AI art can enhance perceptions of human creativity. *Scientific Reports*, 13(1), Article 1. <https://doi.org/10.1038/s41598-023-45202-3>
- Hoshi, H., Fuyama, M., & Ishizu, T. (2025). Mixed emotional structure of paintings. *Psychology of Aesthetics, Creativity, and the Arts*. <https://doi.org/10.1037/aca0000832>
- Hosoya, G. (2020). The artwork and the beholder: A probabilistic model for the joint scaling of persons and objects. *Psychology of Aesthetics, Creativity, and the Arts*, 14(2), 224–236. <https://doi.org/10.1037/aca0000239>
- Hu, J., Zhang, J., Hu, L., Yu, H., & Xu, J. (2021). Art therapy: A complementary treatment for mental disorders. *Frontiers in Psychology*, 12, Article 686005. <https://doi.org/10.3389/fpsyg.2021.686005>
- Huang, M., Bridge, H., Kemp, M. J., & Parker, A. J. (2011). Human cortical activity evoked by the assignment of authenticity when viewing works of art. *Frontiers in Human Neuroscience*, 5. <https://doi.org/10.3389/fnhum.2011.00134>
- Huber, J., Jennissen, S., Nikendei, C., Schauenburg, H., & Dinger, U. (2021). Agency and alliance as change factors in psychotherapy. *Journal of Consulting and Clinical Psychology*, 89(3), 214–226. <https://doi.org/10.1037/ccp0000628>
- Ikotun, A. M., Ezugwu, A. E., Abualigah, L., Abuhaija, B., & Heming, J. (2023). K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data. *Information Sciences*, 622, 178–210. <https://doi.org/10.1016/j.ins.2022.11.139>
- Iosifyan, M., & Wolfe, J. (2024). Everyday life vs art: Effects of framing on the mode of object interpretation. *Empirical Studies of the Arts*, 42(1), 166–191. <https://doi.org/10.1177/02762374231170259>
- Islam, M. R., Ahmed, M. U., Barua, S., & Begum, S. (2022). A systematic review of explainable artificial intelligence in terms of different application domains and tasks. *Applied Sciences*, 12(3), 1353. <https://doi.org/10.3390/app12031353>
- Isrow, Z. (2017). Defining art and its future. *Journal of Arts and Humanities*, 6(6), Article 6. <https://doi.org/10.18533/journal.v6i6.1207>
- Jacobsen, T., & Höfel, L. (2002). Aesthetic judgments of novel graphic patterns: Analyses of individual judgments. *Perceptual and Motor Skills*, 95(3), 755–766. <https://doi.org/10.2466/pms.2002.95.3.755>
- Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters, Award Winning Papers from the 19th International Conference on Pattern Recognition (ICPR)*, 31(8), 651–666. <https://doi.org/10.1016/j.patrec.2009.09.011>
- Jenabi, E., Bashirian, S., Ayubi, E., Rafiee, M., & Bashirian, M. (2023). The effect of the art therapy interventions on depression symptoms among older adults: A meta-analysis of controlled clinical trials. *Journal of Geriatric Psychiatry and Neurology*, 36(3), 185–192. <https://doi.org/10.1177/08919887221130264>

- Choosing a subset of principal components or variables. In Jolliffe, I. T. (Ed.), *Principal component analysis*, (pp. 111–149). (2002) (pp. 111–149). Springer. https://doi.org/10.1007/0-387-22440-8_6.
- Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 374(2065), Article 20150202. <https://doi.org/10.1098/rsta.2015.0202>
- Jordanous, A. (2017). *Co-creativity and perceptions of computational agents in co-creativity*. <https://kar.kent.ac.uk/61658/>.
- Jucker, J.-L., Barrett, J. L., & Włodarski, R. (2014). “I Just Don’t Get it”: Perceived Artists’ intentions affect art evaluations. *Empirical Studies of the Arts*, 32(2), 149–182. <https://doi.org/10.2190/EM.32.2.c>
- Kaube, H., & Abdel Rahman, R. (2024). Art perception is affected by negative knowledge about famous and unknown artists. *Scientific Reports*, 14(1), 8143. <https://doi.org/10.1038/s41598-024-58697-1>
- Kirk, U., Skov, M., Hulme, O., Christensen, M. S., & Zeki, S. (2009). Modulation of aesthetic value by semantic context: An fMRI study. *NeuroImage*, 44(3), 1125–1132. <https://doi.org/10.1016/j.neuroimage.2008.10.009>
- Kitchens, L., & Meier, B. P. (2025). The fearful mind of artificial intelligence: Fear and perceived existential threat of artificial intelligence as a function of its cognitive and emotional capabilities. *The Journal of Social Psychology*, 1–14. <https://doi.org/10.1080/00224545.2025.2503006>
- Kozłowski, A. C., Taddy, M., & Evans, J. A. (2019). The geometry of culture: Analyzing the meanings of class through word embeddings. *American Sociological Review*, 84(5), 905–949. <https://doi.org/10.1177/0003122419877135>
- Kraatz, K., & Xie, S. (2023). Why AI art is not art – A heideggerian critique. *Synthesis Philosophica*, 38(2), 235–253. <https://doi.org/10.21464/sp38201>
- Kuchinke, L., Trapp, S., Jacobs, A. M., & Leder, H. (2009). Pupillary responses in art appreciation: Effects of aesthetic emotions. *Psychology of Aesthetics, Creativity, and the Arts*, 3(3), 156–163. <https://doi.org/10.1037/a0014464>
- Kumar, A. A. (2021). Semantic memory: A review of methods, models, and current challenges. *Psychonomic Bulletin & Review*, 28(1), 40–80. <https://doi.org/10.3758/s13423-020-01792-x>
- Kuška, M., Trnka, R., Kuběna, A. A., & Růžicka, J. (2016). Free associations mirroring Self- and world-related concepts: Implications for personal construct theory, psycholinguistics and philosophical psychology. *Frontiers in Psychology*, 7. <https://doi.org/10.3389/fpsyg.2016.00981>
- Lakens, D. (2022). Sample size justification. *Collabra: Psychology*, 8(1), Article 33267. <https://doi.org/10.1525/collabra.33267>
- Lauring, J. O., Pelowski, M., Forster, M., Gondan, M., Pttio, 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>
- Law, M., Karulkar, N., & Broadbent, E. (2021). Evidence for the effects of viewing visual artworks on stress outcomes: A scoping review. *BMJ Open*, 11(6), Article e043549. <https://doi.org/10.1136/bmjopen-2020-043549>
- 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 & 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>
- Li, Y., & Yang, T. (2018). Word embedding for understanding natural language: A survey. In S. Srinivasan (Ed.), *Guide to big data applications* (pp. 83–104). Springer International Publishing. https://doi.org/10.1007/978-3-319-53817-4_4
- Ma, Y., Cain, K., & Ushakova, A. (2024). Application of cluster analysis to identify different reader groups through their engagement with a digital reading supplement. *Computers & Education*, 214, Article 105025. <https://doi.org/10.1016/j.compedu.2024.105025>
- Ma, L., Chen, D., Feng, Y., Hou, X., & Chen, J. (2024). Emotional conveyance analysis of artificial intelligence painting. *Proceedings of the Eleventh International Symposium of Chinese CHI, CHCHI*, 23, 44–54. <https://doi.org/10.1145/3629606.3629612>
- Magsamen, S. (2019). Your brain on art: The case for neuroaesthetics. *Cerebrum: The Dana Forum on Brain Science*, 2019. cer-07-19.
- Maksimova, A. (2025). Negotiation of dominant AI narratives in museum exhibitions. *AI & Society*, 40(5), 3813–3826. <https://doi.org/10.1007/s00146-024-02140-6>
- Masika, G. M., Yu, D. S. F., & Li, P. W. C. (2020). Visual art therapy as a treatment option for cognitive decline among older adults: A systematic review and meta-analysis. *Journal of Advanced Nursing*, 76(8), 1892–1910. <https://doi.org/10.1111/jan.14362>
- Mastandrea, S., & Crano, W. D. (2019). Peripheral factors affecting the evaluation of artworks. *Empirical Studies of the Arts*, 37(1), 82–91. <https://doi.org/10.1177/0276237418790916>
- Mastandrea, S., Fagioli, S., & Biasi, V. (2019). Art and psychological well-being: Linking the brain to the aesthetic emotion. *Frontiers in Psychology*, 10. <https://doi.org/10.3389/fpsyg.2019.00739>
- Mayring, P. (2021). *Qualitative content analysis: A step-by-step guide*. SAGE Publications Ltd.
- Merriam-Webster. (2025). Definition of ART. <https://www.merriam-webster.com/dictionary/art>.
- Mikalonytė, E. S., & Kneer, M. (2022). Can artificial intelligence make art?: Folk intuitions as to whether AI-driven robots can be viewed as artists and produce art. *ACM Transactions on Human-Robot Interaction*, 11(4), 43:1–43:19. <https://doi.org/10.1145/3530875>
- Mikalonytė, E. S., & Kneer, M. (2023). What is art? The role of intention, beauty, and institutional recognition. *Proceedings of the Annual Meeting of the Cognitive Science Society*, 45(45). <https://escholarship.org/uc/item/9rk3n8xp>.
- Mikalonytė, E. S., & Kneer, M. (2024). The folk concept of art. *Synthese*, 205(1), 2. <https://doi.org/10.1007/s11229-024-04812-8>
- Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. (arXiv:1301.3781). arXiv. <https://doi.org/10.48550/arXiv.1301.3781>
- Miller, C. A., Zhang, K., & Hübner, R. (2025). On the universality of aesthetic preference and inference: A cross-cultural (Chinese–German) study. *Humanities and Social Sciences Communications*, 12(1), 1–19. <https://doi.org/10.1057/s41599-025-04806-y>
- Millet, K., Buehler, F., Du, G., & Kokkoris, M. D. (2023). Defending humankind: Anthropocentric bias in the appreciation of AI art. *Computers in Human Behavior*, 143, Article 107707. <https://doi.org/10.1016/j.chb.2023.107707>
- Mondal, B. (2020). Artificial intelligence: State of the art. In V. E. Balas, R. Kumar, & R. Srivastava (Eds.), *Recent trends and advances in artificial intelligence and internet of things* (pp. 389–425). Springer International Publishing. https://doi.org/10.1007/978-3-030-32644-9_32
- Neef, N. E., Zabel, S., Papoli, M., & Otto, S. (2024). Drawing the full picture on diverging findings: Adjusting the view on the perception of art created by artificial intelligence. *AI & Society*. <https://doi.org/10.1007/s00146-024-02020-z>
- Newman, G. E., & Bloom, P. (2012). Art and authenticity: The importance of originals in judgments of value. *Journal of Experimental Psychology: General*, 141(3), 558–569. <https://doi.org/10.1037/a0026035>
- Newman, G. E., & Smith, R. K. (2018). Artworks are evaluated as extensions of their creators. In F. Cova, & S. Réhault (Eds.), *Advances in experimental philosophy of aesthetics* (1st ed.). Bloomsbury Publishing Plc.
- Nordgren, L. F., van Harreveld, F., & van der Pligt, J. (2006). Ambivalence, discomfort, and motivated information processing. *Journal of Experimental Social Psychology*, 42(2), 252–258. <https://doi.org/10.1016/j.jesp.2005.04.004>
- Nosek, B. A., Ebersole, C. R., DeHaven, A. C., & Mellor, D. T. (2018). The preregistration revolution. *Proceedings of the National Academy of Sciences*, 115(11), 2600–2606. <https://doi.org/10.1073/pnas.1708274114>
- Palmer, S. E., Schloss, K. B., & Sammartino, J. (2013). Visual aesthetics and human preference. *Annual Review of Psychology*, 64, 77–107. <https://doi.org/10.1146/annurev-psych-120710-100504>
- Papenmeier, F., Dagit, G., Wagner, C., & Schwan, S. (2024). Is it art? Effects of framing images as art versus non-art on gaze behavior and aesthetic judgments. *Psychology of Aesthetics, Creativity, and the Arts*, 18(4), 642–653. <https://doi.org/10.1037/aca0000466>
- Park, J., Kang, H., & Kim, H. Y. (2023). Human, do you think this painting is the work of a real artist? *International Journal of Human-Computer Interaction*, 1–18. <https://doi.org/10.1080/10447318.2023.2232978>
- Parker, C., Scott, S., & Geddes, A. (2019). *Snowball sampling*. SAGE Research Methods Foundations. <https://doi.org/10.4135/9781526421036831710>
- Pelowski, M., & Akiba, F. (2011). A model of art perception, evaluation and emotion in transformative aesthetic experience. *New Ideas in Psychology*, 29(2), 80–97. <https://doi.org/10.1016/j.newideapsych.2010.04.001>
- Pelowski, M., Forster, M., Tinio, P. P. L., Scholl, M., & Leder, H. (2017). Beyond the lab: An examination of key factors influencing interaction with ‘real’ and museum-based art. *Psychology of Aesthetics, Creativity, and the Arts*, 11(3), 245–264. <https://doi.org/10.1037/aca0000141>
- Pelowski, M., Gerger, G., Chetouani, Y., Markey, P. S., & Leder, H. (2017). But is it really art? The classification of images as “Art”/“Not Art” and correlation with appraisal and viewer interpersonal differences. *Frontiers in Psychology*, 8. <https://doi.org/10.3389/fpsyg.2017.01729>
- Pennington, J., Socher, R., & Manning, C. (2014). Glove: Global vectors for word representation. *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*. <https://doi.org/10.3115/v1/D14-1162>
- Pike, A. W. G., Hoffmann, D. L., García-Díez, M., Pettitt, P. B., Alcolea, J., De Balbín, R., González-Sainz, C., De Las Heras, C., Lasheras, J. A., Montes, R., & Zilhão, J. (2012). U-Series dating of Paleolithic art in 11 caves in Spain. *Science*, 336(6087), 1409–1413. <https://doi.org/10.1126/science.1219957>
- Plisiecki, H., & Sobieszek, A. (2024). Emotion topology: Extracting fundamental components of emotions from text using word embeddings. *Frontiers in Psychology*, 15. <https://doi.org/10.3389/fpsyg.2024.1401084>
- Purhonen, S., Verboord, M., Sirkka, O., Kristensen, N. N., & Janssen, S. (2023). Definitely (not) belonging to culture: Europeans’ evaluations of the contents and limits of culture. *Poetics*, 101, Article 101840. <https://doi.org/10.1016/j.poetic.2023.101840>
- Rabb, N., Brownell, H., & Winner, E. (2018). Essentialist beliefs in aesthetic judgments of duplicate artworks. *Psychology of Aesthetics, Creativity, and the Arts*, 12(3), 284–293. <https://doi.org/10.1037/aca0000174>
- Rafner, J., Beaty, R. E., Kaufman, J. C., Lubart, T., & Sherson, J. (2023). Creativity in the age of generative AI. *Nature Human Behaviour*, 7(11), 1836–1838. <https://doi.org/10.1038/s41562-023-01751-1>
- Raunak, V. (2017). *Simple and Effective Dimensionality Reduction for Word Embeddings* (arXiv:1708.03629). arXiv. <https://doi.org/10.48550/arXiv.1708.03629>
- Raunak, V., Gupta, V., & Metz, F. (2019). *Effective Dimensionality Reduction for Word Embeddings* (pp. 235–243). Association for Computational Linguistics. <https://doi.org/10.18653/v1/W19-4328>
- Reber, R., Schwarz, N., & Winkielman, P. (2004). Processing fluency and aesthetic pleasure: Is beauty in the perceiver’s processing experience? *Personality and Social Psychology Review*, 8(4), 364–382. https://doi.org/10.1207/s15327957pspr0804_3

- Reymond, C., Pelowski, M., Opwis, K., Takala, T., & Mekler, E. D. (2020). Aesthetic evaluation of digitally reproduced art images. *Frontiers in Psychology*, 11, Article 615575. <https://doi.org/10.3389/fpsyg.2020.615575>
- Reynolds, A. P. F., & Ricciardi, E. (2024). Subjective emotional instances surpass formal perceptual features in shaping the aesthetic appeal of artworks. *Psychology of Aesthetics, Creativity, and the Arts*. <https://doi.org/10.1037/aca0000720>
- Rodriguez Novo, N., Novo Muñoz, M. M., Cuellar-Pompa, L., & Rodriguez Gomez, J. A. (2021). Trends in research on art therapy indexed in the web of science: A bibliometric analysis. *Frontiers in Psychology*, 12. <https://doi.org/10.3389/fpsyg.2021.752026>
- Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*, 20, 53–65. [https://doi.org/10.1016/0377-0427\(87\)90125-7](https://doi.org/10.1016/0377-0427(87)90125-7)
- Russell, S., & Norvig, P. (2020). *Artificial intelligence: A modern approach* (4th ed.). Pearson.
- Salas Espasa, D., & Camacho, M. (2025). From aura to semi-aura: Reframing authenticity in AI-generated art—a systematic literature review. *AI & Society*, 40(8), 6727–6759. <https://doi.org/10.1007/s00146-025-02361-3>
- Samo, A., & Highhouse, S. (2023). Artificial intelligence and art: Identifying the aesthetic judgment factors that distinguish human- and machine-generated artwork. *Psychology of Aesthetics, Creativity, and the Arts, No Pagination Specified-No Pagination Specified*. <https://doi.org/10.1037/aca0000570>
- Shirkhorshidi, A. S., Aghabozorgi, S., Wah, T. Y., & Herawan, T. (2014). Big data clustering: A review. In B. Murgante, S. Misra, A. M. A. C. Rocha, C. Torre, J. G. Rocha, M. I. Falcão, D. Tanar, B. O. Apduhan, & O. Gervasi (Eds.), *Computational science and its applications – ICCSA 2014* (pp. 707–720). Springer International Publishing. https://doi.org/10.1007/978-3-319-09156-3_49
- Sigmundsson, H., Haga, M., & Hermundsdottir, F. (2020). The passion scale: Aspects of reliability and validity of a new 8-item scale assessing passion. *New Ideas in Psychology*, 56, 100745. <https://doi.org/10.1016/j.newideapsych.2019.06.001>
- Song, L., Zhang, G., Ma, L., Silvennoinen, J., & Cong, F. (2025). Comparative analysis of color emotional perception in art and non-art university students: Hue, saturation, and brightness effects in the munsell color system. *BMC Psychology*, 13(1), 650. <https://doi.org/10.1186/s40359-025-03034-y>
- Specker, E., Tinio, P. P. L., & van Elk, M. (2017). Do you see what I see? An investigation of the aesthetic experience in the laboratory and museum. *Psychology of Aesthetics, Creativity, and the Arts*, 11(3), 265–275. <https://doi.org/10.1037/aca0000107>
- Spee, B. T. M., Pelowski, M., Arato, J., Mikuni, J., Tran, U. S., Eisenegger, C., & Leder, H. (2022). Social reputation influences on liking and willingness-to-pay for artworks: A multimethod design investigating choice behavior along with physiological measures and motivational factors. *PLoS One*, 17(4), Article e0266020. <https://doi.org/10.1371/journal.pone.0266020>
- Stamkou, E., Keltner, D., Corona, R., Aksoy, E., & Cowen, A. S. (2024). Emotional palette: A computational mapping of aesthetic experiences evoked by visual art. *Scientific Reports*, 14(1), Article 19932. <https://doi.org/10.1038/s41598-024-69686-9>
- Szubielska, M., & Imbir, K. (2021). The aesthetic experience of critical art: The effects of the context of an art gallery and the way of providing curatorial information. *PLoS One*, 16(5), Article e0250924. <https://doi.org/10.1371/journal.pone.0250924>
- Szubielska, M., Imbir, K., & Szymańska, A. (2021). The influence of the physical context and knowledge of artworks on the aesthetic experience of interactive installations. *Current Psychology*, 40(8), 3702–3715. <https://doi.org/10.1007/s12144-019-00322-w>
- Tigre Moura, F., Castrucci, C., & Hindley, C. (2023). Artificial intelligence creates art? An experimental investigation of value and creativity perceptions. *Journal of Creative Behavior*, 57(4), 534–549. <https://doi.org/10.1002/jocb.600>
- Tinio, P. P. L., & Gartsu. (2018). Characterizing the emotional response to art beyond pleasure: Correspondence between the emotional characteristics of artworks and viewers' emotional responses. In *Progress in brain research* (Vol. 237, pp. 319–342). Elsevier. <https://doi.org/10.1016/bs.pbr.2018.03.005>
- Tjasink, M., Keiller, E., Stephens, M., Carr, C. E., & Priebe, S. (2023). Art therapy-based interventions to address burnout and psychosocial distress in healthcare workers—A systematic review. *BMC Health Services Research*, 23(1), 1059. <https://doi.org/10.1186/s12913-023-09958-8>
- Tripathy, J. S., Singh, A., & Tripathy, D. (2026). The Double-Edged Sword of Consecutive and Snowball Sampling: Practical Utility Versus Methodological Compromise. *Indian Journal of Psychological Medicine*, 48(1), 81–84. <https://doi.org/10.1177/02537176251405469>
- Trupp, M. D., Bignardi, G., Specker, E., Vessel, E. A., & Pelowski, M. (2023). Who benefits from online art viewing, and how: The role of pleasure, meaningfulness, and trait aesthetic responsiveness in computer-based art interventions for well-being. *Computers in Human Behavior*, 145, Article 107764. <https://doi.org/10.1016/j.chb.2023.107764>
- Trupp, M. D., Howlin, C., Fekete, A., Kutsche, J., Fingerhut, J., & Pelowski, M. (2025). The impact of viewing art on well-being—A systematic review of the evidence base and suggested mechanisms. *The Journal of Positive Psychology*, 20(6), 978–1002. <https://doi.org/10.1080/17439760.2025.2481041>
- Vallerand, R. J., Blanchard, C., Mageau, G. A., Koestner, R., Ratelle, C., Léonard, M., Gagné, M., & Marsolais, J. (2003). Les passions de l'âme: On obsessive and harmonious passion. *Journal of Personality and Social Psychology*, 85(4), 756–767. <https://doi.org/10.1037/0022-3514.85.4.756>
- van Harreveld, F., van der Pligt, J., & de Liver, Y. N. (2009). The agony of ambivalence and ways to resolve it: Introducing the MAID model. *Personality and Social Psychology Review*, 13(1), 45–61. <https://doi.org/10.1177/1088868308324518>
- van Paasschen, J., Bacci, F., & Melcher, D. P. (2015). The influence of art expertise and training on emotion and preference ratings for representational and abstract artworks. *PLoS One*, 10(8), Article e0134241. <https://doi.org/10.1371/journal.pone.0134241>
- Vartanian, O. (2022). The contributions of emotion and reward to aesthetic judgment of visual art. In A. Chatterjee, & E. Cardilo (Eds.), *Brain, beauty, and art: Essays bringing neuroaesthetics into focus*. Oxford University Press. <https://doi.org/10.1093/oso/9780197513620.003.0017>
- Wagner, V., Menninghaus, W., Hanich, J., & Jacobsen, T. (2014). Art schema effects on affective experience: The case of disgusting images. *Psychology of Aesthetics, Creativity, and the Arts*, 8(2), 120–129. <https://doi.org/10.1037/a0036126>
- Wang, Y., & Ma, H. (2019). The value evaluation of artificial intelligence works of art. 2019 international joint conference on information, media and engineering (IJCIME) (pp. 445–449). <https://doi.org/10.1109/IJCIME49369.2019.00096>
- Wang, C., & Xiao, A. (2025). Anxiety induced by artificial intelligence (AI) painting: An investigation based on the fear acquisition theory. *Psychological Trauma. Theory, Research, Practice, and Policy*, 17(Suppl 1), S214–S224. <https://doi.org/10.1037/tra0001862>
- Westerman, R. (2018). Intentionality and the aesthetic attitude. *British Journal of Aesthetics*, 58(3), 287–302. <https://doi.org/10.1093/aesthj/ayy010>
- Wolz, S. H., & Carbon, C.-C. (2014). What's wrong with an art fake? Cognitive and emotional variables influenced by authenticity status of artworks. *Leonardo*, 47(5), 467–473. https://doi.org/10.1162/LEON_a_00869
- Zaidel, D. W. (2010). Art and brain: Insights from neuropsychology, biology and evolution. *Journal of Anatomy*, 216(2), 177–183. <https://doi.org/10.1111/j.1469-7580.2009.01099.x>
- Zhang, B., Wang, J., & Abdullah, A. binti (2024). The effects of art therapy interventions on anxiety in children and adolescents: A meta-analysis. *Clinics*, 79, Article 100404. <https://doi.org/10.1016/j.clinsp.2024.100404>
- Zhao, Y., Li, T., Wang, H., & Li, C. (2025). Visual art therapy for cognitive and emotional enhancement in aging and dementia: A structured narrative review. *Journal of Alzheimer's Disease Reports*, 9, Article 25424823251383728. <https://doi.org/10.1177/25424823251383728>
- Zhou, Y., & Kawabata, H. (2023). Eyes can tell: Assessment of implicit attitudes toward AI art. *I-Perception*, 14(5), Article 20416695231209846. <https://doi.org/10.1177/20416695231209846>
- Zubala, A., Pease, A., Lyszkiewicz, K., & Hackett, S. (2025). Art psychotherapy meets creative AI: An integrative review positioning the role of creative AI in art therapy process. *Frontiers in Psychology*, 16. <https://doi.org/10.3389/fpsyg.2025.1548396>