AI or Art? – Can we learn to differentiate between AI Imagery and Art?

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Abstract

Artificial Intelligence (AI) produced content is entering our lives in many ways, including exposure to AI images. This is leading to issues of indistinguishability. Issues range from fraud to feared job loss due to copyright infringements. The present research tested whether the difference between AI Images and art can be learned. A spaced interleaved inductive learning paradigm was used to train participants in the experimental condition, then all participants were tested on their ability to distinguish between AI imagery and art. In the test, participants were shown an image and had to indicate whether it was an AI image or art. After exclusion, our study had 82 participants. The results show that said learning paradigm can be used to train people to distinguish between AI imagery and art. The bias against AI was replicated and we found no individual differences moderating the training effect. These findings might help with the development of training programs to differentiate AI images and art. We suggest, that real-life encounter learning might take place, leading to people being able to tell if they see an AI image. Future research could look at new insights into the qualitative differences between AI imagery and art, the bias surrounding them, as well as individual differences that could enlarge the training effect.

Keywords: Art, AI images, Artificial intelligence, AI, Inductive learning, Midjourney, spaced interleaved inductive learning paradigm

AI or Art? – Can we learn to differentiate between AI Imagery and Art?

Artificial Intelligence (AI) produced content is entering our lives in many ways, including exposure to AI images. This is due to recent advances, and popularity, in AI tools, including image generation. The generated images can have qualities that make them indistinguishable from human-made art. Multiple scandals involving AI imagery have taken place already. An example of this is when the world was deceived by AI images showing the ex-president of the US, Donald Trump being arrested (Devlin & Cheetham, 2023). AI images are being used in creative ways to scam people (DiResta & Goldstein, 2024). Artists have a harder time finding small jobs, which can be vital for their portfolios, as designs and AI images are flooding social media (Shaffi, 2023; DiResta & Goldstein, 2024). On a more philosophical level, artists state creativity cannot be replaced by machines. This is because the AI imagery is taking images from large accessible databases and mixing them together, instead of engaging in the creative process (Shaffi, 2023). Among these databases, there are copyrighted images. Mimicking a style is frowned upon and may be considered copyright infringement in the artistic community (Shaffi, 2023). The emergence of AI imagery raises copyright issues and the risk of financial or political fraud and job loss and therefore might also foster distrust or fear towards displayed art or images. However, AI imagery tools are still quite a novel phenomenon, and it may be the case that people can learn to appreciate the subtle differences as the technology becomes more common – i.e., as they become more exposed to it. People may simply develop an intuition about whether an image is AI-generated or not. If this is the case, then exposure to a learning paradigm should make people better at distinguishing between them.

As people are more exposed to AI imagery, they may develop a feeling for what features might make them distinct from art. Those features may include variances in novelty, expressed skill, emotional expressiveness, aesthetic appeal, and cultural significance (Ulger, 2020; Christiaans, 2002; Grant, 2019). Arguably human artists are currently able to capture these aspects better than AI, especially regarding emotional expressiveness and cultural significance. Based on this, humans could be taught to pick up these differences and distinguish AI from art. This phenomenon is called inductive learning. Inductive learning can be described as learning a new concept or category by observing, therefore using a bottom-up approach. It should enable people to come up with an implicit theory on what differentiates AI imagery from art. One meta-analysis by Nugroho et al. (2021) showed inductive learning-based modules to be effective, as they increase critical thinking skills in science learning. It has also been used and shown to be effective in establishing a learning effect in the context of art concept differentiation. In a study by Kornell and Bjork (2008), paintings of different artists were presented, and participants were able to inductively distinguish them. We used an inductive learning paradigm in this study because it mimics real-life encounters with AI imagery. The inductive learning paradigm suggests that the exposure over time might establish a learning effect and this means that people gain an ability to recognize AI imagery.

Training people to distinguish between different forms of imagery can best be achieved with a spaced, interleaved design of the inductive learning paradigm. In an interleaved design, stimuli of different categories/ different artists are presented in turn. Kornell and Bjork's (2008) research on inductive learning in the context of art category differentiation emphasizes the difference in effectiveness between the two main paradigms in inductive learning: spacing and massing. Both terms describe how often, and with how much time in between, art stimuli are presented. Spacing in inductive learning would mean that the stimuli are presented more spaced out, with more time in between. Participants learn by remembering features that stand out. Massing on the other hand means all similar stimuli are presented together. Here participants learn by finding similarities between the presented art. Kornell and Bjork (2008) found that spacing resulted in better inductive learning than massing. This effect was shown through a post-test image recognition test, indicating that spacing benefits apply to complex learning tasks. Despite participants rating massing as more effective, their performance demonstrated the opposite, suggesting a misjudgement from the participants (Kornell & Bjork, 2008). Kornell and Bjork's findings were replicated, confirming the advantage of spacing over massing in inductive learning (Verkoeijen & Bouwmeester, 2014). Furthermore, Kang & Pasher (2011) found that the spaced, interleaved design, is more effective in the context of differentiating art compared to temporal spacing (presenting the same artist's paintings with time in between). Likely this difference is due to the increased discriminative contrast between the different categories. Thus, if people can indeed learn to distinguish between AI imagery and art better, an inductive interleaved design yields a better result.

Hypothesis 1: People exposed to an interleaved inductive learning paradigm are more accurate in distinguishing between AI imagery and art.

It appears that people have a negative attitude towards AI-generated images. But does that show in their behaviour? Chamberlain and colleagues (2018) and Ganghadharbathla et al (2022) have found that people are more likely to rate images they like more as art and identified a bias against AI imagery. Not liking an image on the other hand might lead them to wrongly rate the image as AI-generated.

Hypothesis 2: Artworks that are liked more, will more often be indicated as AI imagery.

Those with previous Art knowledge should acquire more accuracy from the training. The Vienna Art Interest and Art Knowledge (VAIAK) Questionnaire (Specker et al., 2020) gives insight into previous art knowledge, with its specific focus on art and depth of knowledge assessment. Prior Knowledge was found to influence the amount and type of information observers learned about visual Art (Koroscik, 1982) while also influencing the learning outcome in training (Shapiro, 2004). Chamberlain and colleagues (2018) found a non-significant difference between Art-educated and non-educated people in the accuracy of identifying AI imagery. Though not significant, this might give a hint towards a relevant prior knowledge gap between art-educated and non-educated people. The difference might not have been significant because age could have been a moderating factor, as the art-educated people were older than the non-educated people. Therefore, art knowledge might be significantly related to identifying AI imagery and could also amplify the effect of the exposure learning. Similarly, familiarity with AI imagery might enable people to benefit more from the training. It is possible that those with AI imagery familiarity already have a better understanding of its distinct qualities. Shapiro (2004) suggests that this understanding could serve as a foundation for the integration of further knowledge and skills. This is in line with Koroscik´s finding that people learn more about visual art if they know more beforehand (1982). Those with AI imagery familiarity should have a larger increase in accuracy following the exposure to the spaced interleaved inductive learning paradigm.

Hypothesis 3: Those with previous art knowledge or AI imagery familiarity should benefit more from the exposure to the spaced interleaved inductive learning paradigm.

Earlier studies that investigated if people could tell if imagery is AI or art, did not apply training to investigate if it is possible to teach participants to make the distinction between AI imagery and art (Samo & Highhouse, 2023; Chamberlain et al., 2018; Gangadharbatla, 2022; Ragot et al., 2020). The findings of these studies suggest that people can not differentiate between AI imagery and art. Samo and Highhouse (2023) provided participants with a single image, of which they had to tell if it was AI or art. They concluded that people are unable to accurately identify the artwork's source. While this seems to be the case for a one-time exposure, it remains unclear if people are unable to correctly identify an artwork´s source with a better understanding of AI imagery. Using a larger set of items, Chamberlain et al. (2018) found that people performed slightly above chance level.

Training people successfully with inductive learning to differentiate between AI imagery and art could lead to more transparency and trust regarding the use of AI. We hypothesize that we will find a small effect size. This is however a promising result, as the training we applied in the experiment was not very extensive. This could mean, that with more practice the training might yield a larger effect. Alternatively, people naturally learn to distinguish art over time, as they get more exposed to AI imagery. The results of this research could help the development of a training program to help distinguish between AI and art. This could allow media and art creators or journalists to tackle the problem of what is AI and what is not. Those professionals might be able to influence the media landscape in a way that leads to a more mature and benevolent incorporation of AI imagery.

Methods

Participants

The sample contained participants collected via the SONA-systems platform from first-year psychology students at the University of Groningen, who received course credits for their participation, as well as participants recruited through convenience sampling based on the social network of the authors. There were 100 participants who completed the study. Data cleaning included removing 18 participants who gave insufficient answers (i.e. below 20). The final sample used in this study therefore consisted of 82 participants. No demographic data was recorded.

Design of the Stimuli

A set of 120 images was compiled, consisting of 60 AI images and 60 non-AI images, meaning art that was created without the use of an AI image generator. The AI imagery was created with the software package MidJourney (Version 6) in March 2024. An example of a prompt is [/imagine old renaissance portrait of a 14th-century peasant] or [/imagine oil on canvas landscape after sundown, with a vibrant, purple, but still realistic sky, depicting a slightly hilly, clean but picturesque field. in the style of Herman van Swanevelt]. A full list of prompts is in Appendix A. Through this process, images were created in three categories: abstract, portraits, and landscape. Twenty images were selected for each category, equalling a total of 60 AI images. This selection was made by voting among the researchers, on the basis that the selected images should fulfill the following requirements: they should not be easily identifiable as AI-generated images, and there should be some variety within the respective categories.

The traditional artworks were selected from a variety of sources. Most of the images were sourced from the website of the Metropolitan Museum of Art, while some additional images were found from other websites.

Procedure & Measures

The participants were asked to complete the study online, on the platform Qualtrics. At the start of the experiment, the participants were asked to fill out the questionnaires about art knowledge and about AI imagery familiarity, which were adapted from the Vienna Art Interest and Art Questionnaire Knowledge (VAIAK) (Specker et al., 2020).

Art Knowledge

For the assessment of art interest and knowledge, we used a 7-item scale based on Specker and colleagues' (2020) Vienna Art Interest and Art Knowledge Questionnaire (VAIAK). Artistic interest was measured across two scales, with four items capturing self-reported interest rated on a 7-point Likert scale (1 = *not at all*, 7 = *very much*) and three behavioural items rated on a 7-point frequency scale (1 = *less than once per year*; 7 = *once per week or more often*). The self-reported art interest scale included items such as: “I am interested in art” and “I am always looking for new artistic impressions and experiences”. Examples of the behavioural items are: “How often do you visit art museums and/or galleries?” and “How often do you read books, magazines, or catalogues about art?”. The internal consistency of the artistic interest scale that was used in this study was good (α = 0.86).

AI Imagery familiarity

For the assessment of AI imagery familiarity, we adapted the VAIAK scale (Specker et al., 2020) to ask about AI imagery instead. We adapted the items in such a way that the new scale measures self-reported AI imagery familiarity using four items rated on a 7-point Likert scale (1 = *not at all*, 7 = *very much*) and three behavioural items regarding AI imagery rated on a 7-point frequency scale (1 = *less than once per year*; 7 = *once per week or more often*). The self-reported AI imagery familiarity scale included items such as: “I am interested in AI art technology” and “I like to talk about AI art technology with others”. Examples of the behavioural items are: “I´m always looking for new AI art Impressions and experiences?” and “How often do you seek out AI art technology?”. The internal consistency of the AI imagery familiarity scale that was used in this study was good (α = 0.80).

After the completion of these questionnaires, participants were given the instructions for the experiment itself. The experimental group and the control group were given partially different instructions, as the experimental group was asked to complete both a training and a testing procedure, while the control group was only asked to complete the testing procedure. However, the testing procedure was identical for both groups.

The experimental group was first asked to observe the images that appeared on the screen. Then, the images were shown, each with a label showing whether the image is AI or art. Each artwork was shown for a duration of 5 seconds; with 2 seconds of break in between the stimuli. In total 78 artworks were shown, of which 39 were AI and 39 art. Within the AI and art pool 13 portrait artworks, 13 landscape artworks, and 13 abstract artworks were presented. The order of the presentation followed the interleaved spaced design of inductive learning (Kang & Pasher, 2011). An AI image was always followed by an artwork, and vice versa. After all the images were shown, the training part of the experiment was over. Participants in the experimental condition were able to take a short break and continue with the testing phase.

In the testing part of the experiment, all participants were asked to guess whether the images they were presented with one by one, another set of 42 images, were AI or art.

Image Classification

The classification of images as AI images or art was captured with a single item: “This image is...”. There were two response options (“Painted by a person” or “AI-generated”). Participant’s confidence in their classification was also assessed using a single item asking: “How certain are you in your judgment?” on a slider from 0 to 100.

They were also asked to indicate how much they liked each image; a Likert scale was applied. Each image was presented together with the two scales. Like in the training set, the pool contained an equal number of images from each subcategory; but it consisted of a different set of images. After participants in the experimental group were finished with the test, they were asked to write any remark or feedback about the experiment if they wished to. Finally, they could see a message thanking their participation, which marked the end of the procedure.

Results

All hypotheses were tested using ANOVA (analysis of variance), multiple regression, or the t-test procedure. Assumptions for ANOVA and multiple regression are met. The Shapiro-Wilk test showed that the assumption of normality is not violated in both conditions, Control-Condition: $W(47) = 0.985$, $p = .794$; Condition 1: $W(35) = 0.978$, $p = .702$ (Table 1). The inspection of the Q-Q plots resulted in the same conclusion (Figure 1). Homogeneity of variances was tested using Levene's test, which showed that the variances were equal across conditions $F(1,80) = 0.463$, $p = .498$ (Table 2). To check the assumptions for the independent samples t-test, the Shapiro-Wilk test was used to check the assumption of normality W = 0.97, p = .385, and AI images W = 0.93, p = .009 (Table 7). The assumption of normality is partially met. Levene´s test was used to check the assumption of homogeneity, which was satisfied, F (1,82) = 0.087, p = .768 (Table 8). Due to the violation of the assumption of normality, a Mann-Whitney U test W = 203.500, p < .001 (Table 9) was run.

To test hypothesis 1 (H1) an ANOVA was conducted. The relative number of correct responses to total responses (percent correct) was entered as the dependent variable, and the group belonging was entered as the independent variable. The results of the ANOVA were consistent with Hypothesis 1 (H1). People exposed to the interleaved inductive learning paradigm were more accurate in the discrimination between AI images and art, F(80) = 8.853, p = .004 (Table 3). The 95% Confidence interval for the mean difference of 6.5% is [2.2%, 10.8%] (Table 4). The training had a small effect on accuracy, η_{p^2} = .1 (Table 3).

To test hypothesis 2 (H2), an independent samples t-test was conducted with the dependent variable being the liking rating, and as an independent variable the classification of the images by the participants. The mean liking score for classified art was M = 4.81, SD = 0.51, and for AI images M = 3.92, SD = 0.51 (Table 5). Consistent with Hypothesis 2 (H2) there was a significant difference between the averages of the liking scores of classified AI images and classified art t(82) = -7.92, p < .001 (Table 6). Due to the violation of the assumption of normality, a Mann-Whitney U test W = 203.500, p < .001 (Table 9) was run, to make sure the found difference is robust against the violation. To determine if the actual AI images were liked less, a paired samples t-test was run, featuring the variable pair of averaged liking scores for AI images and art. Participants liked AI images more M = 4.515, SD = 0.683 than art M = 4.231, SD = 0.678 (Table 10). The difference here was significant t(24) = -2.202, p = .038 (Table 11).

To test Hypothesis 3 (H3), a multiple regression analysis was run to test if art knowledge or AI imagery familiarity has a moderating effect on the relationship between the training and the ability to correctly identify an AI image. The dependent variable is the proportion of correct answers on the AI image items and the independent variables are Art knowledge, AI imagery familiarity, and the interaction effects between those and the presence of exposure to the spaced interleaved inductive learning paradigm. The interaction terms between the presence of exposure to the spaced interleaved inductive learning paradigm and art knowledge $B = 0.018$, $SE = 0.027$, $t = 0.663$, $p = .510$) (Table 12) and between the presence of exposure to the spaced interleaved inductive learning paradigm and AI imagery familiarity $B = -0.038$, $SE = 0.03$, $t = 1.269$, $p = .208$ (Table 12) were not significant.

Discussion

The purpose of this study was to see if a spaced interleaved inductive learning paradigm could train people to distinguish between AI imagery and art. The hypothesis (H1) that training improves the ability to make that distinction was supported by our main finding. Without training, participants performed at a chance level, suggesting that we have no innate capacity to distinguish between AI imagery and art. The bias against AI imagery was confirmed (H2). AI imagery obtained higher average liking ratings. However, participants rated images they thought were AI imagery less positively. The findings did not support our third hypothesis (H3), which said that prior art knowledge or AI imagery familiarity would moderate the training effect.

In previous research Kang and Pasher (2012) used the spaced interleaved inductive learning paradigm to train art category differentiation. Our findings expand on this research by applying the paradigm (Kang & Pasher, 2012) to AI imagery. The findings of earlier research on AI imagery and art differentiation (Samo & Highhouse, 2023; Chamberlain et al., 2018; Gangadharbatla, 2022; Ragot et al., 2020) were partly replicated. They stated that people cannot differentiate between AI imagery and art. Our results supported these findings, however, we found that there are improvements to the ability to differentiate after training. The bias against AI imagery found by Chamberlain and colleagues (2018) and Gangadharbatla (2022) was supported by our findings.

Our findings' most important practical implication is that people can learn to distinguish AI imagery from art by being exposed to the right learning paradigm. The spaced interleaved inductive learning paradigm we used, mimics real-life encounters. This suggests that over time, people will learn to differentiate AI imagery from art through real-life encounters. This skill could be useful in a wide variety of professional and non-professional contexts due to the increasing importance of AI. The training effect also suggests that there are qualitative differences between AI imagery and art. We can conclude this because the spaced interleaved inductive learning paradigm enables people to pick up on patterns in AI imagery. It is still unclear which individual differences could enhance the training effect, as the hypothesised art knowledge and AI imagery familiarity did not explain any part of the training effect.

A strength of our study is that the spaced interleaved inductive learning paradigm mimics real-life scenarios. This allows us to draw conclusions about real-life scenarios based on our results. Another strength of our study is regarding the stimuli used. The AI images were carefully chosen and difficult to distinguish from art. The main strength is that our study fills the research gap of training in AI imagery differentiation.

The main limitation of our study is the selection of our stimuli. As we selected both the AI and non-AI stimuli as a group, we aimed to make the stimuli difficult to distinguish. We could have been biased and selected the images based on certain properties that are not representative of AI imagery or art. This could have led to the participants not having picked up on the AI characteristics in the images, but rather on the properties that we selected them for. Another limitation is the small size of our sample and that it was acquired conveniently. More noteworthy results might have been identified with a larger sample. Another limitation might be the validity of our proposed moderators. From everything we know about inductive learning, prior knowledge in the field should have predicted a better learning outcome (Koroscik, 1982; Shapiro, 2004). Both AI imagery familiarity and art knowledge did not have that moderating effect. This suggests that there might be issues with the conceptualization of AI imagery familiarity and art knowledge. We do not know what kind of knowledge specifically would help with the learning outcome, as the field is new.

Where exactly future research is needed stays unclear, as the field is rapidly changing. However, assuming that the technology will progress further we have some suggestions. Future research could explore the qualitative differences between AI imagery and art. It could be investigated if the learning effect still applies after real artists work on the AI prompts, therefore including features of creativity. That way it could be tested if the qualitative difference consists, in part, of a lack of creative effort in AI imagery. The qualitative differences might change as technology advances and that could also be of interest. The training effect we found could be replicated by future research, to further strengthen our findings. Future research could also look at how participants distinguish between AI imagery and art to find out about the qualitative differences. Research could explore whether there is a learning effect from real-life encounters with AI imagery in longitudinal studies. There could be factors working against this proposed real-life encounter learning effect. Those could entail an aversion towards AI imagery or that AI imagery is not always marked as such. Both these factors could be explored to be able to make better propositions about the impact AI imagery might have.

The results support that a spaced interleaved inductive learning paradigm can be used to train people to distinguish between AI imagery and art. This could potentially help with the development of training programs to help differentiate AI images and art. We suggest, that real-life encounter learning might take place, and people might be able to tell if they see an AI image. However, that remains to be seen or tested. Future research promises new insights into the qualitative differences between AI imagery and art, the bias surrounding them, and individual differences that could enlarge the training effect.

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Tables and Figures

Table 1

Descriptive Statistics

	Percent correct	
	Control group	**Experimental group**
Valid	47	35
Missing	3	10
Mean	0.509	0.573
Std. Deviation	0.094	0.102
Shapiro-Wilk	0.985	0.978
P-value of Shapiro-Wilk	0.794	0.702
Minimum	0.310	0.313
Maximum	0.750	0.786

Note. Excluded 4 rows from the analysis that correspond to the missing values of the split-by variable Condition

Table 2

Test for Equality of Variances (Levene's)

F	**df1**	**df2**	**p**
0.463	1.000	80.000	0.498

Table 3

ANOVA – Percent correct

Cases	**Sum of Squares**	**df**	**Mean Square**	**F**	**p**	**η^2**	**η^2_p**
Condition	0.085	1	0.085	8.853	0.004	0.100	0.100
Residuals	0.764	80	0.010				

Note. Type III Sum of Squares

Table 4

Simple Contrast - Condition

	95% CI for Mean Difference

Comparison	Estimate	Lower	Upper	SE	df	t	p
1 - 0	0.065	0.022	0.108	0.022	80	2.975	0.004

Table 5

Descriptive Statistics

	Liking	
	Art	**AI imagery**
Valid	42	40
Missing	0	0
Mean	3.918	4.813
Std. Deviation	0.515	0.525
Minimum	3.000	3.432
Maximum	5.000	5.640

Note. Excluded 17 rows from the analysis that correspond to the missing values of the split-by variable Rating

Table 6

Independent Samples T-Test

	t	df	p
Liking	-7.787	80	< .001

Note. Student's t-test.

Table 7

Test of Normality (Shapiro-Wilk)

		W	p
Liking	1	0.926	0.010
	2	0.970	0.358

Note. Significant results suggest a deviation from normality.

Table 8

Test of Equality of Variances (Levene's)

	F	df_1	df_2	p
Liking	0.017	1	80	0.896

Table 9

Independent Samples T-Test

	W	df	p
Liking	203.500		< .001

Note. Mann-Whitney U test.

Table 10

Descriptives

	N	Mean	SD	SE	Coefficient of variation
LikingArt	39	4.231	0.678	0.109	0.160
LikingAIImages	38	4.515	0.683	0.111	0.151

Table 11

Paired Samples T-Test

Measure 1	Measure 2	t	df	p	Cohen's d	SE Cohen's d
LikingArt	LikingAIImages	-2.202	24	0.038	-0.440	0.120

Note. Student's t-test.

Table 12

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	0.541	0.017		30.995	< .001
H_1	(Intercept)	0.508	0.025		20.167	< .001
	ArtKnowledge	-0.014	0.020	-0.105	-0.692	0.491
	AIImageryFamiliarity	0.030	0.019	0.220	1.596	0.115
	AIImageryFamiliarity *Condition	-0.038	0.030	-0.218	-1.269	0.208
	Artknowledge*Condition	0.018	0.027	0.100	0.663	0.510
	Condition (1)	0.098	0.044		2.221	0.029

[a] Standardized coefficients can only be computed for continuous predictors.

Table 13

Pearson's Correlations

Variable		SC0relative	ArtKnowledge	AIImageryFamiliarity
1. percent correct	Pearson's r	—		
	p-value	—		
2. ArtKnowledge	Pearson's r	-0.090	—	
	p-value	0.424	—	
3. AIImageryFamiliarity	Pearson's r	-0.063	-0.142	—
	p-value	0.572	0.166	—

Figure 1

Q-Q Plot

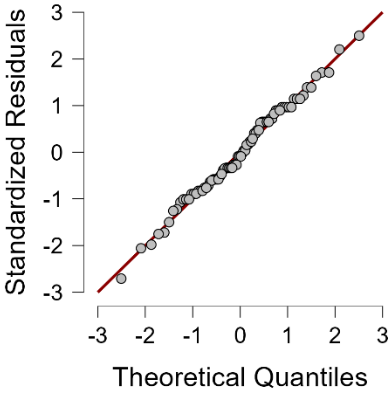


Figure 2

Boxplot of mean differences in accuracy

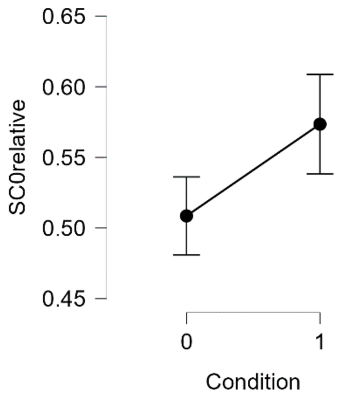
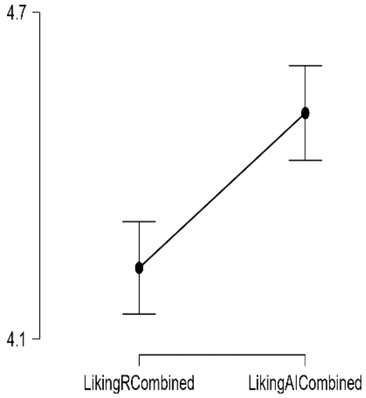


Figure 3

Boxplot of mean differences in liking



Appendix A

AI image creation prompts

Abstract

abstract, oil on canvas painting like Max de Winter's Monkey Business, that is seemingly unstructured at first glance, but does have from human-ish shapes that come together in the strokes, which are not too obvious. the colours should be a little bit darker than in the original work.
multiple abstract modern paintings
multiple abstract modern paintings
multiple abstract modern paintings
abstract oil on canvas paining in the style of abreesha jones, using the same brushes as the artist does.
abstract oil on canvas painting in the style of lisa carney. use the same paining technques and brushes as the artist
oil on canvas paninting exactly like this but with slightly different shapes and arrangement

abstract but realistically structured, oil on canvas painting that seems to resemble a futuristic, dystopian, but slightly humorous city. sophisticated use of brush and strokes
abstract painting of intertwined zebra's filling up the entire frame only in black and white, figurative, victor vasarely
Agamograph by Yaacov Agam
an abstract painting
an abstract painting
an abstract painting
an abstract painting
an abstract painting
an abstract painting
an abstract painting
Homage to the Square by Josef Albers
minimalistic abstract painting in this style, without any shapes of humans or anything figurative. should suggest the feeling of falling apart

simple, abstract painting, using different shades of orange, also playing with the strenght of pushing the brush against the canvas. and simple repeating patterns of hexagons, in a neat, simple arrangement. should represent the feeling of coming together.

Landscape

Simon Stålenhag
oil on canvas landscape in sunrise, depicting a flat, clean but picturesque field. in the style of Richmond Castle.
a landscape painting that looks like meindert hobbema's work
a landscape painting that looks like meindert hobbema's work
a landscape painting that looks like meindert hobbema's work
a landscape painting that looks like peter paul rubens' work.
april gornik dunes behind savanna monotonous sky
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a landscape painting that looks like peter paul rubens' work.
a landscape painting that looks like peter paul rubens' work.
erin hanson cherry blossom
erin hanson arbor of light
oil on canvas landscape after sundown, with a vibrant, purple, but still realistic sky, depicting a slightly hilly, clean but picturesque field. in the style of Herman van Swanevelt.
oil on canvas landscape in sunrise, depicting a flat, clean but picturesque field. in the style of Richmond Castle.
april gornik wheatfield with monotonous dark sky and a tree
fine brush painting on canvas in the style of Jacob van Ruisdael, depicting a river, rocks, and a small waterfall.
fine brush painting on canvas in the style of Jacob van Ruisdael, depicting a river, rocks, and a small waterfall.
a brush painting of a rainy dutch forest and farmland, in the style of peter paul rubbens.
a brush painting of a rainy dutch forest and farmland, in the style of peter paul rubbens.

Portraits

portrait 18th century rococo neoclassicism grand manner chiaroscuro sfumato pastoral patronage allegory physiognomy gaze drapery vanitas face
francisco de goya
create an oil portrait of John the baptist using the alla prima painting technique on canvas make sure that the face is painted using the underpainting technique
create an oil portrait of marie antoinette using the alla grisaille technique on canvas make sure that the face is painted using the underpainting technique
create an oil portrait of John the baptist using the impasto technique on canvas make sure that the face is painted using the underpainting technique
create a full body portrait of John the Baptist in front of the Jordan River using the alla prima technique on canvas, make sure that the face is painted using the underpainting technique
create a full-body oil portrait of Moses holding the Ten Commandments using the alla prima technique on canvas, and make sure that the face is painted using the underpainting technique

create a full-body oil portrait of Moses holding the Ten Commandments written on stone tablets in an impressionist style using the alla prima technique on canvas, and make sure that the face is painted using the underpainting technique
a baroque style oil on paint portrait of a merchant
paint a portrait of a merchant, standing in front of cart, using oil paints on canvas and the impasto painting technique
a baroque-style oil on canvas portrait of a monk
old renaissance portrait of a 14th century peasant
old renaissance portrait of a 15th century wealthy man
a portrait painting, that looks like Rembrandt's work
painted portrait old dark canvas oil beggar
a dark and old-fashioned full-body oilpainting on canvas portrait of Anne Hutchinson in the style of Rembrandt
a dark and old-fashioned full-body oilpainting on canvas portrait of Anne Hutchinson in the style of Rembrandt
old renaissance portrait of a wealthy merchant 15th century
paint a baroque-style oil on canvas portrait of a young, 17th-century princess standing in an orchard
paint a baroque-style oil on canvas portrait of a young, 17th-century princess standing in an orchard

Human-made picture titles

Abstract

Orange Blossom-Lisa Carney
Homage to the square- Joseph Albers
Healing Antenna- Matthew Dibble
Monkey business- Max de Winter
Told you so!- Max de Winter
The Trendsetter- Max de Winter
Typografie Design- Henry Stazewski
Relief- Henry Stazewski
Vicky Barranguet- All about you
Jeffrey Tover- Coachella Valley
Naomi Yuki- Cosmos, Inside
Victor Vasarely- Zebras
Sonia Delaunay- Electric Prisms
Jeffery Tover- Los Angeles
Jeffrey Tover- Night Ride
Vicky Barranguet- Nothing held back
Vicky Barranguet- Roads not taken
Paul Franklin- Turquoise Moon
Kazimir Malevich- Dynamic Suprematism

Landscape

Haystacks: Autumn - Jean-Francois Millet

Landscape Study with Clouds - Emile Loubon
Cuckmere Haven - Eric Ravilious
Grainfields - Jacob van Ruisdeel
Landscape by Moonlight - Peter Paul Rubens
Landscape - Circle of Carl Rottmann
Mountainous Landscape at Vicovaro - Simon Denis
The Waterspout - Gustave Courbet
View of Tivoli from Santa Maria del Giglio - Leon Fleury
The Alley at Middelharnis - Meindert Hobbema
Meindert Hobbema- Watermolen
Achille Etna Michallon- Waterfall at Mont-Dore
Eugene Isabey- Sunset on the Normandy Coast
Simon Denis- On the Quirinal Hill
R.S. Duncan- Savanna
Philip Wilson Steer- Richmond Castle, Yorkshire
Eric Hanson- Cherry Blossom
Simon Stalenhag- The Mascot
Claude Lorrain- Sunrise
Paul Cezanne- Viaduct of the Arc River Valley

Portrait

Portrait of an Unknown Woman - Ivan Kramskoy
Jean-Baptiste Faure - Edouard Manet
Reading Woman - Ivan Kramskoy
Comtesse de la Châtre - Élisabeth Vigée Le Brun
Archbishop of Milan - Tiziano Vecellio
Portrait of Dmitri Vasilievich Grigorovich - Ivan Kramskoy
Francois Gerard - Antoine-Jean Gros
FLINT OIL ON LINEN 2017 (MISSING)
The Love Letter - Jean-Honore Fragonard
Samuel P. Avery - Raimundo de Madrazo y Garreta
Portrait of a man - Unknown artist
Lady Elizabeth Stanley - George Romney
Portrait of Louis-Félix Amiel - Eugène Devéria
Lucia - Frederic Leighton
Portrait of a Man - David Bailly
Portrait of Claes Duyst van Voorhout - Frans Hals
Sibylle - Corot
Marie Joséphine Charlotte du Val d'Ognes - Marie Denise Villers
Mrs. Richard Bache - John Hoppner
Portrait of a Child - Camille Corot

Vienna Art Interest and Knowledge Questionnaire (VAIAK) (Specker et al., 2020)

1. I like to talk about art with others.

2. I’m interested in art.

3. I’m always looking for new artistic impressions and experiences.

4. In everyday life I routinely see art objects that fascinate me.

5. How often do you visit art museums and/or galleries?

6. How often do you read books, magazines or catalogs about art?

7. How often do you look at images of artworks (catalogs, internet, etc.)?

Vienna Art Interest and Knowledge Questionnaire (VAIAK) (Specker et al., 2020), Adapted AI Scale

1. I like to talk about AI art technology with others.

2. I’m interested in AI art technology.

3. I’m always looking for new AI art impressions and experiences.

4. In everyday life I see AI art that fascinates me.

5. How often do you seek out AI art technology?

6. How often do you read articles about AI art technology?

7. How often do you look at AI artwork and images (e.g. on the internet, etc.)?