Who Can Tell if It's AI? Using Inductive Learning to Distinguish AI Art and Traditional Art

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Abstract

Frequently, generative AI has seen a massive spike in attention and influence. People are more and more confronted with AI-generated content, especially artworks. This development sparked debate not only about the sophistication of AI and difficulty distinguishing its content, but also about whether an AI can really mimic human creativity. We intended to investigate this in order to see whether we could potentially train participants to get better at distinguishing between traditional and AI-generated artworks, and on the other hand whether participants higher in art knowledge would benefit more from the training. 35 participants in the experimental condition received an online inductive learning paradigm, and then completed a test where they had to indicate whether a presented picture was made with AI or not. Relative to the 47 participants in the no-training control condition, results confirm our first hypothesis, as they show that the experimental condition was significantly better at correctly identifying the source of the artwork during the test. However, contrary to our second hypothesis, art knowledge did not seem to have an influence on this relationship. Despite the apparent sophistication of AI, these results suggest that there still might be something in us that enables us to notice AI-generated content, given proper training. Next to some strengths, such as exploratory work in a highly relevant field, some limitations such as sample limitations and the online environment are also discussed. Future research should address these issues by conducting laboratory experiments and improving the sample by focusing on art experts.

Who Can Tell if It's AI? Using Inductive Learning to Distinguish AI Art and Traditional Art

The release of Open AI's software ChatGPT at the end of 2022 marked a milestone in the usage of and attention towards generative AI in the general public, which can be seen in the increasingly high numbers of search interest in the term "ChatGPT" on Google (Fui-Hoon Nah et al., 2023). Apart from text-generating AI software packages such as ChatGPT, also image-generating software packages such as MidJourney emerged. MidJourney is able to generate pictures as well as art in seconds just on the basis of simple text prompts, requiring minimal effort and skill. These effortless requirements make the possibilities endless for people to create art. However, this also sparked two major discussions in the scientific community and the general public.

The first point of discussion was that people started wondering about the fact that AI is becoming more and more sophisticated and this might lead to problems, with AI potentially someday replacing creative professionals (Joshi, 2023). A striking example of this happened in 2022, when an AI-generated art piece won a prize at an art competition in the US (Roose, 2022). Understandably, some people in the artistic community were not happy about this result. Given the development of these sophisticated AI software packages, one might wonder whether AI-generated pictures and traditional pictures have become so hard to distinguish from another that people cannot immediately recognize AI-generated pictures. With the possible further advancement of AI technology in the future, being able to tell apart which is which is going to become a vital skill in everyday life.

The second point of discussion was an argument about what human creativity even is exactly, and whether AI can capture this (Kirkpatrick, 2023). Interestingly, there is some initial evidence present that people might be negatively biased against AI-generated artwork, (Bellaiche et al., 2023). However, it is questionable if this bias is also evident in people's judgments. If people are presented with a picture that is possibly either AI-generated or made with traditional methods, it could be that this bias also translates into their classification in one of these two categories. Therefore, in this study we will focus on whether people are able to distinguish AI-generated artworks from traditional artworks, and whether they can learn to get better at it with training. We aim to shed light on this issue by investigating whether we can actively train participants via an inductive learning approach to distinguish between the two forms of artworks.

Sophistication of AI Images

Given current developments, it seems safe to assume that the use of Artificial Intelligence (AI) and its generated contents is going to become more and more important in our future lives. A revolutionary landmark in this regard was the release of the software package ChatGPT on 30th of November 2022, which attracted a tremendous amount of attention all over the world (Fui-Hoon Nah et al., 2023). However, not only the attention for ChatGPT specifically was very high, but also the broader category generative AI. What followed very soon were discussions about the implementation of generative AI in various fields such as education (Baidoo-Anu & Ansah, 2023), public health (Biswas, 2023), and marketing (Rivas & Zhao, 2023). Subsequently, AI software packages such as MidJourney emerged, which is currently one of the leading AIs when it comes to creating pictures and artworks based on text prompts. In order to use MidJourney, minimal skill requirements are needed, which opens up the possibilities for anyone to create sophisticated art. While this brings many benefits, it also brings about some problems. For example, people are frequently fooled by AI-generated art, which can be seen in incidental reports of AI-generated pictures winning art competitions (Roose, 2022). Naturally, the skill of being able to accurately distinguish between what is AI-made and what is traditionally made shifts into focus. This might be especially true in the context of propaganda and other politicized subjects. Sheer logic and knowledge of human nature tells us that the possibilities for misinterpretation and misinformation due to abuse of AI-generated content are endless (Blauth et al., 2022). Given this information, it becomes clear that people need to be able to recognize AI-generated art.

AI and Human Creativity

The prior mentioned rise of image-generating AI also challenged the traditional concepts of creativity. For example, Simon (2001, p.208) stated that “we judge thought to be creative when it produces something that is both novel and interesting or valuable”. The degree to which an AI software package such as MidJourney creates something new and valuable (and is therefore by definition creative) is questionable, as it uses already existing pictures to develop output. A reasonable assumption would be that generative AI might be able to create content that has to deal with more arithmetic or cognitive tasks, but is not able to accurately grasp emotional aspects like creativity. In the end, people assume that it is creativity that separates us from machines (Gangadharbatla, 2022). In line with this are the results found by Millet and colleagues (2023) supporting a negative bias against AI art: they found that the same artwork is preferred less simply because it was labeled as AI-made (vs. traditional), due to the fact that it was perceived as less creative. There might be a fundamental emotional layer inherent in creativity and art that even an AI might not be able to recreate, and people might notice this missing piece. For example, Kirkpatrick (2023) states that “Despite the ability of AI to produce creative outputs based on the attributes of existing works, the process is not the same as a human's creativity, which comes from a combination of real-world experience, emotion, and inspiration.” As already hinted at, one of the important qualities of art is that it’s used to convey and elicit emotions in the viewer (Barwell, 1986). Can this really be done by AI, which is in the end just a very sophisticated computer algorithm? And are humans really different from this? If they are, then this should be noticeable in the artworks they create. Interestingly, already existing evidence suggests that people are not very good at correctly identifying the artwork source (either AI or traditional) but that they nevertheless prefer the human art and experience more positive emotions in response to them (Samo & Highhouse, 2023). Taken all of this together, this might serve as a hint that there is still something in the art that is an expression of something within us, which is then what we subconsciously recognize. At first glance it may seem similar, but something essential is missing. All in all, if there are in fact actual differences, people should be able to tell the difference between AI-made art and traditional art, based on the AI's lack of emotional qualities and creativity.

Inductive Learning

If there really is a difference between AI-generated and traditional artworks, people should be better able to tell apart the differences as they get more exposed to it. In essence, this is called inductive learning, defined as "learning to generalize from relevant prior encounters" (Kang & Pashler, 2012). In other words, this means that through repeated exposure people learn over time to pick up on subtle details between stimuli, often without really being able to point out those subtle differences. Connecting this to the present study, people might not be able to define and connect the different stimuli to variation in creativity. Despite all of this, if there truly is this difference - no matter what it actually is - people should be able to learn to spot it, even if they cannot report on what the difference is. After years of research on inductive learning, evidence emerged that pointed out the optimal presentation of stimuli in such an inductive learning paradigm: researchers generally found that interleaving the stimuli (i.e. arranging stimuli so that they are temporarily separated from each other) is more effective than massing them (i.e., arranging the stimuli from the same category in blocks; Kornell & Bjork, 2008; Sun et al., 2022). This result was then called the interleaving effect on inductive learning (Sun et al., 2022). Moreover, Zulkiply and Burt (2013) found that interleaving is especially beneficial for low-discriminability categories. As the differences between AI-generated and traditional artworks are likely going to be very subtle (i.e. low discriminability), an inductive learning paradigm with interleaving stimuli would be very feasible. For example, Kornell and Bjork (2008) already studied this in the context of art, including stimuli with low discriminability, and were successful in their findings. Putting it all together, if there truly is a difference between the two categories, people should be able to learn to spot it, as exposure to AI-generated content increases. This brings us to the first hypothesis of our study:

Hypothesis 1: There is a positive effect of inductive training on accuracy. Specifically, those exposed to inductive learning can more accurately distinguish between traditional and AI-generated artworks, compared to those who receive no training.

Art Knowledge May Moderate the Effect of Training

In addition to any effect of training on accuracy, there are individual differences that could moderate how much individuals benefit from the training. One of these moderating factors and the focus of this study might be artistic background knowledge. In general, there is evidence out there that having more extensive background knowledge and deep understanding about something increases attentional abilities (Ericsson et al., 1993). For example, Gobet & Campitelli (2007) found that chess expertise and domain-specific knowledge can lead to enhancements in attentional control and performance. Furthermore, there is evidence that individuals need relevant background knowledge to effectively engage with new material in the same domain (Kirschner et al., 2006). According to the presented evidence it could be very likely that extensive background knowledge on art leads to better domain-specific attentional abilities, which in turn could mean that those participants in the training condition pick up on the differences between AI-generated art and traditional art during the inductive learning phase more easily. All in all, this leads us to the second hypothesis of our study:

Hypothesis 2: we expect that there is a significant positive effect of the inductive training on subsequent accuracy at correctly identifying traditional artworks and AI-made artworks, and that this effect is even stronger for people that are high in artistic background knowledge.

Methods

Participants

On one part, the sample (N = 100) contained participants collected via the SONA-systems platform from first-year psychology students at the University of Groningen (n = 35), who received course credits for their participation. The other participants were recruited through convenience sampling based on the social network of the authors. Eighteen participants gave insufficient answers (i.e. below 20) and were removed from the data set. 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-generated pictures and 60 traditional artworks. The AI-generated artworks were created with the 6th version of the software package Midjourney (2024). All 60 AI stimuli were created by the researchers 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 pictures were created in three categories: abstract art, portraits, and landscape art. Twenty pictures were selected for each category, equaling a total of 60 AI-generated images. This selection was made by voting among the researchers, on the basis that the selected pictures 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 (The Metropolitan Museum of Art, n.d.), while some additional images were found from other websites. Again, we opted for 20 pictures from each of the previously mentioned categories.

Procedure & Measures

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

Art Knowledge

For the assessment of art interest, 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 behavioral 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 behavioral items are: "How often do you visit art museums and/or galleries?" and "How often do you read books, magazines or catalogs about art?". The obtained internal consistency of the art knowledge scale was satisfactory (α = 0.863).

After the completion of the questionnaire, participants were given 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 artworks that appeared on the screen. Then, the artworks were shown, each with a label showing whether the artwork is AI or non-AI. 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 were non-AI. Within the AI and non-AI-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, 2012). An AI artwork was always followed by a non-AI artwork, and *vice versa.* After all the artworks 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 artworks they were presented with one by one, another set of 42 artworks, were AI or non-AI.

Image Classification

The classification of images as AI-art or traditional art was captured with a single item: “This image is …”. There were two response options (“Painted by a human” or “AI-made”). 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 artwork; a Likert-scale was applied. Each artwork was presented together with the two scales. Like in the training set, the pool contained an equal number of artworks from each subcategory; but it consisted of a different set of artworks. 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

Descriptive Statistics

Table 1 shows that the mean percentage of correct answers in the testing phase was higher for the training condition (M = 57.3, SD = 10.2) than for the no-training condition (M = 50.9, SD = 9.4), indicating some positive effect of training. Furthermore, this table shows that participants in the control condition essentially performed at chance level. Figure 1 visualizes this difference in a box plot. In this plot, the difference in means can be clearly observed. What is also interesting to note is that the maximum data point in the control condition (i.e., 75%) is featured as an outlier. Surprisingly, the data also show a negative correlation between art knowledge and test performance, although this relationship is non-significant (r = -.095, p = .398). This result does not provide any evidence in support of hypothesis 2, which predicted that there would be a significant positive correlation between art knowledge and test performance.

Hypothesis Testing

An ANCOVA was conducted to test both of our hypotheses (Table 2). Accuracy was entered as the dependent variable, and the condition of the participants plus art knowledge as the independent variables, including their interaction. Regarding hypothesis 1 (whether there was an effect of training on subsequent test performance), results suggest that there is indeed a significant group difference between the training and no-training condition (F (1, 77) = 8.762, p = .004). As can be seen in Figure 1, this indicates that the prior inductive learning paradigm helped these participants to correctly identify AI-generated and traditional artworks in the testing phase better than participants in the control condition. Furthermore, the partial eta squared value shows that about 10% of the variance in the data can be explained by the participants' belonging to the different conditions (η_p^2 = .102). All in all, these results clearly support our first hypothesis.

Regarding hypothesis 2 (whether people with more art knowledge gain more from the inductive learning phase), results seem to contradict our hypothesis. Art knowledge does not seem to have an influence on how much people benefit from the training, which can be seen in the non-significant values for the interaction effect between art knowledge and the condition (F(1, 77) = .690, p = .409). Moreover, partial eta squared hints at only 0.9% of explained variance due to this interaction (η_p^2 = .009). More detailed information regarding the effect estimates for both hypotheses can be found in Table 3. Taken everything together, our proposed individual difference variable does not add anything towards the already established main effect, thereby disconfirming our second hypothesis.

Exploratory Analysis

The data revealed that multiple participants completed the study on a mobile device rather than a PC (Table 4). This could mean that doing the experiment on a desktop would pose a benefit for participants, because the pictures are bigger and potentially also in a higher resolution, which could increase accuracy. However, the ANOVA presented in Table 5 shows that no significant differences were found ($F(1, 80) = .003$, $p = .955$). The device on which the participants completed the study did not make a difference when it comes to test performance.

Discussion

The present study aimed to investigate the effect of an inductive learning paradigm in the context of training to get better at distinguishing between AI-generated and traditional artworks. Participants in the training condition first completed a training phase, where they were presented with interleaved AI-generated and traditional artworks, which were also marked as such. After that, they were asked to complete a test where they had to identify whether a presented artwork was made with AI or traditional methods. To compare the results, participants in the control condition completed the test without prior training.

Our first hypothesis was that participants in the training condition would be more accurate during the testing phase at correctly identifying AI-generated and traditional artworks. The results obtained from the data clearly showed that this hypothesis was supported: in the experimental condition there was indeed a significant positive effect of training on subsequent test performance, when compared to the control condition. Our second hypothesis was that this positive effect of training is even stronger for participants high in art knowledge, suggesting that they take away more from the training than participants low in art knowledge. In this case, the data did not support the hypothesis: there was no statistically significant relationship between art knowledge and subsequent test performance.

Sophistication of AI Images

An important underlying aspect of this study is the question of whether AI has already become so good that AI-generated art can potentially fool people. Prior research in this context already suggested that people are unable to correctly identify artwork source when comparing human- and machine-generated art (Samo & Highhouse, 2023). Our results are in line with that, as can be seen in the rate of about 51% correct guesses among participants in the control group.

This result has important theoretical and practical implications. Firstly, people already often cannot distinguish between AI-made pictures and traditional pictures, and this is not just something that might happen in the future. It is already a problem in our present time. Given the logical suggestion that AI is only going to get better with time, fear of AI is justified to some degree and is likely going to increase in the future. When it comes to practical implications, worries about AI replacing artists that create pictures seems also justified to some degree. When facing the potential decision of buying and hanging up an artwork, there might be some people who would rather go for the cheaper and easier option of just creating a picture with AI themselves, since people do not seem to be able to tell the difference anyways. This could potentially lower the value of art created nowadays. The possible consequences of this are at the present time hard to predict.

AI and Human Creativity

Another important aspect of this study is the question of whether AI can really be creative like humans (Gangadharbatla, 2022; Kirkpatrick, 2023). Moreover, it is clear that AI has challenged the traditional view on human creativity (Simon, 2001). It would be a reasonable assumption that AI can not mimic the inherent emotional layer given in art made with traditional methods. Our obtained results could support this notion: with proper training, people learned to pick up on the differences between AI-generated and traditional artworks.

An interesting theoretical implication of this would be that there indeed seems to be some quality of the AI-generated artworks that still differentiates them from traditional art. It could be that with training people learn to subconsciously pick up on the lack of emotions and creativity in the AI pictures, which makes them in turn easier to identify. From a practical point of view it can be said that AI algorithms such as Midjourney, while they are undoubtedly good, may not be able to copy all of the aspects of traditional art and still seem to be lacking in some features. Our results have shown that with training, people potentially notice these missing aspects. Whether you could augment these AI software packages to include human emotions and creativity or if this is just impossible, is at this point questionable.

Inductive Learning

The theoretical basis for the improvement that was proposed to take place in the experimental condition was inductive learning. Prior evidence already supports this effect in different contexts and with different studies (Kornell & Bjork, 2008; Sun et al., 2022). Our present study further replicated these findings, which can be seen in the confirmation of our first hypothesis: the inductive training paradigm had a significant positive effect on subsequent test performance. A theoretical implication would be that our study replicates prior results and further strengthens the support for inductive learning as a successful learning strategy. However, our study also adds some new insights, namely that inductive learning also extends towards the context of AI-generated pictures and that it does also work there. Furthermore, we also confirmed that the interleaving effect with low-discriminability categories indeed works with AI-made and traditional-made artworks. An important practical implication of these results could be that based on inductive learning specific training protocols for the general public could be developed, which would be aimed at improving AI literacy and identifying AI-generated content. The extent to which this is actually realizable is however still to be determined.

Art Knowledge May Moderate the Effect of Training

A crucial point of investigation for us was the investigation of an individual difference variable that influences how much people in the experimental condition benefit from the training. In line with this, our second hypothesis proposed art knowledge as such a potential moderator, because there was some general evidence out there that having more knowledge in an area increases attention (Ericsson, 1993) and enables you to effectively deal with new material in the same domain (Kirschner et al., 2006). However, in this study we could not find support for this hypothesis.

From a theoretical perspective, it could be that the proposed link between art knowledge and gaining more from the training phase was somehow flawed and that some other crucial variables were not accounted for. It could also be that while the general link between being an expert and better attention in that field may hold, for some unknown reason art knowledge specifically may not follow this pattern. Additionally, an important practical implication of our results would be that experts with more knowledge in art do not gain anything more from the training. They would need to complete a training protocol just like everyone else, as results suggest that being high in art knowledge does not necessarily make a difference.

Strengths and Limitations

Although only one of our two hypotheses turned out to be supported, the present study still has some noticeable strengths to offer. Firstly, the quality of the generated AI stimuli was extremely good, as our data shows that participants had substantial difficulties recognizing the AI-generated artworks. Secondly, we still found a significant main effect, even though our study did not have high statistical power due to the limited sample size. This suggests that the underlying effect may be genuinely strong. Finally, our study was exploratory in a young and interesting field of research, which also has some direct and very important practical implications for our daily lives. This fact makes our study very relevant, and our study can also serve as a starting point for further research in that area. Next to the strengths of our study, also a few limitations have to be mentioned. The first limitation deals with the sample: our final sample size after data cleaning consisted of only 84 participants in total. Moreover, we also used convenience sampling to get our participants, so that there were mostly young students included. One could assume that these young people already have a lot of contact with AI content. Another limitation was that the study was carried out online and not in a laboratory, suggesting that there might be a variety of uncontrollable variables that might have an influence on the results. Connected to this point is that participants used different devices with different browsers to finish the study, therefore they also had different resolutions of the pictures. The resolutions of the pictures might also have had an influence on the classification of the images. Finally, all of the AI images were made with only one software package during a specific time period. There is a lot of variety in terms of quality of the generated pictures, depending on which version of which software package you use. Moreover, the authors also made a selection on which pictures to use, potentially including some bias. These limitations should be addressed in future research.

Future Research

Since this study was an early and exploratory one, there are a number of potential points to focus on in the future. Firstly, the sample needs to be discussed. A higher sample size would be needed, in order to potentially also detect an interaction effect with our moderator. A sample that includes half experts in arts (e.g. art students), and half people with average levels of art knowledge would provide more insight into the hypothesized effect of art knowledge. Secondly, a follow-up study should take place in a laboratory setting, in order to limit the influence of confounding variables and standardize important aspects of the procedure, like the size and resolution of the stimuli. Thirdly, the AI-generated stimuli should be representative of the AI stimuli encountered in the real world and include stimuli generated from multiple AI software packages. A pilot study on a large pool of pictures could initially be run to see which pictures are the best. All in all, this study has opened up some exciting new points of inquiry for the future.

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Tables and Figures

Table 1

Descriptive Statistics

	Condition	
	0	1
Valid	47	35
Mean	50.854	57.348
SD	9.409	10.249
Minimum	30.953	31.250
Maximum	75.000	78.571

Note. 0 indicates control condition, 1 indicates experimental condition

Figure 1

Boxplot

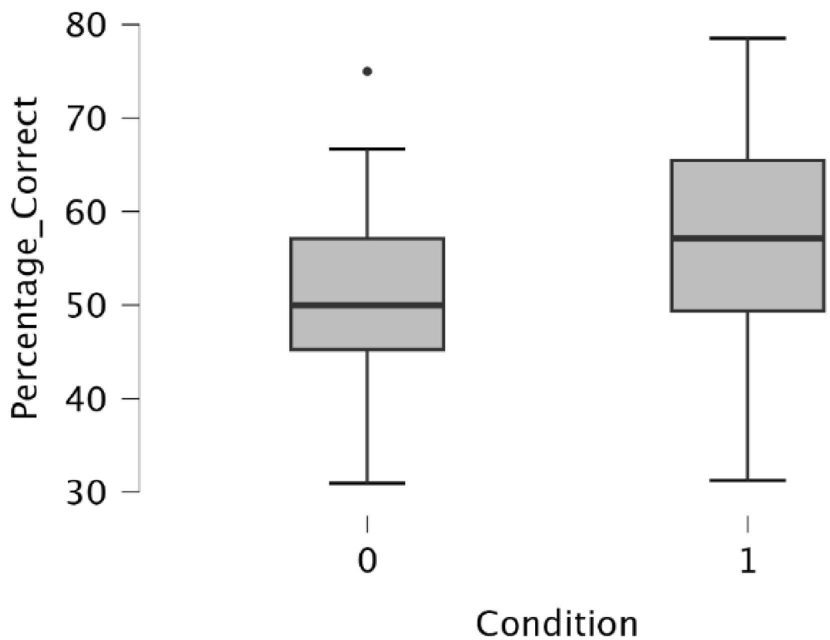


Table 2

ANCOVA Table

Cases	Sum of Squares	df	Mean Square	F	p	η_p^2
Condition	829.372	1	829.372	8.762	0.004	0.102
ArtKnowledge	39.991	1	39.991	0.422	0.518	0.005
Interaction	65.303	1	65.303	0.690	0.409	0.009
Residuals	7288.409	77	94.655			

Note. Type 3 Sum of Squares

Table 3

Effect Estimates

							95% CI	
	Model	Unstandard.	SE	Standard.	t	p	Lower	Upper
H_0	(Intercept)	53.465	1.133		47.191	<0.001	51.210	55.720
H_1	(Intercept)	50.823	1.467		34.646	<0.001	47.902	53.744
	Condition (1)	6.523	2.204		2.960	0.004	2.135	10.911
	ArtKnowledge	-0.189	0.186	-0.159	-1.019	0.311	-0.559	0.181
	Interaction	0.212	0.256		0.831	0.409	-0.297	0.721

Table 4

Descriptive Statistics Split by Device

	Device	
	Desktop	Phone
Valid	44	38
Mean	53.566	53.696
SD	11.300	9.003
Minimum	30.952	31.707
Maximum	78.571	73.810

Table 5

ANOVA Table

Cases	Sum of Squares	df	Mean Square	F	p
Device	0.346	1	0.346	0.003	0.955
Residuals	8489.298	80	106.116		

Note. Type 3 Sum of Squares

Appendix

AI picture 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

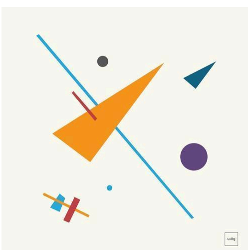
an abstract painting

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

april gornik dunes behind savanna monotonous sky april gornik dunes behind savanna monotonous sky

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)

3. I like to talk about art with others.

7. I'm interested in art.

9. I'm always looking for new artistic impressions and experiences.

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

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

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

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