Can We Unlearn to Get Tricked? An Inductive Learning Approach to Distinguish Between AI Paintings and Traditional Paintings

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Abstract

Without training, people fail to reliably distinguish between AI artworks and human-made artworks. This experiment aims at investigating whether it is possible to teach people to distinguish between AI artwork and human-made artwork by using a spaced inductive learning paradigm. The first hypothesis states that an inductive learning approach, combined with spacing, can teach people to better distinguish between AI artworks and human-made artworks. The second hypothesis states that people who are more interested in arts benefit more from the training compared to participants who are less interested in arts. To investigate the hypotheses, an experiment was designed and conducted on Qualtrics. The final data includes responses of 82 participants, most of them being University of Groningen first-year Psychology students. Overall, participants who received training were 57,3% accurate in identifying the creation process of a picture. An ANCOVA yielded a significant result for the first hypothesis (p = 0.004; η_p^2 = 0.102). Therefore, evidence was found that a spaced inductive learning paradigm can teach people to better distinguish between AI artworks and human-made artworks. There was no evidence found about an interaction effect between art interest and training effectiveness (p = 0.409). Thus, people high in art interest do not seem to benefit more from the training. Even with training, participants' ability to distinguish is still close to chance level in our sample. Therefore, an improved training might be necessary to reliably teach people to detect a difference. However, more developed AI artwork creating software might counter improvements in response accuracy in the future.

Keywords: Inductive Learning, AI art, Creative AI, Art recognition

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The field of artificial intelligence (AI) has already had a huge impact on people's lives. AI takes over many roles humans were responsible for in the past as it influences a broad variety of applications such as self-driving cars, different types of service robots, smart homes, and an advanced search engine called ChatGPT (Ertel, 2018). AI is an extremely fast-moving field, but it is still in its beginning (Schneider & Rea, 2018). The impact of AI will only become bigger as the technology progresses. One of the areas in which AI technologies are applied is artwork creation. Traditionally, artworks have been created manually by an artist. Nowadays, with the help of a user's input, computers can create artwork through AI software such as Midjourney (Holz, 2022). Midjourney is AI artwork-producing software that currently creates the most promising results and was initially released in July 2022. AI artworks are difficult to distinguish from human-made artworks[1] (Samo & Highhouse, 2023). Learning how to be able to distinguish between AI pictures and real pictures may be an important tool to protect oneself from deception. There have already been past occurrences where internationally famous people uploaded AI-generated pictures to their social media. Donald Trump, for example, uploaded an AI-generated picture to his Instagram profile showing him praying in a kneeling manner in a church. Also, Kate Middleton, the Princess of Wales, uploaded a picture that was criticized as either heavily edited or AI-created. Furthermore, creating fake evidence with AI pictures or public media using computer-generated pictures to influence the general population might be two additional areas of deceptive AI picture applications. Criminals could create fake evidence to use in a court to win a trial. Political parties could use deceptive AI pictures as a means of propagating their ideas. This underlines the importance of being able to distinguish between AI-generated

[1] Throughout the thesis, I will refer to AI artwork as AIA, and to human-made artwork as HA.

pictures and human-made pictures not only on an individual level but also on a collective level and yields the research question: Can we unlearn to get tricked?

AI-generated images are still a very novel technology, and early research suggests that people are not very good at distinguishing whether art was made by a human being or by AI. Samo and Highhouse (2023) found that participants in their study were 60% accurate in assessing whether an artwork was made with AI or by a human. In their study, Samo & Highhouse used DALL-E generated pictures and compared them with pictures of human artists. When the study was conducted, it is our considered opinion that artwork creation with DALL-E was not as advanced as it is today with Midjourney (Holz, 2022). Thus, an accuracy of 60% might even be too high for today's standard and this number might be lower with the artwork creation ability of today's software. Chamberlain et al. (2018) conducted a similar study and found a mean accuracy of only 52.49%. These results were not significantly different from the chance level of correctly identifying a picture (50%). Furthermore, Gangadharbatla (2022) found that out of the five AI-generated artworks they presented in their study, only one was correctly identified as an AI artwork by most of the participants. In their study, participants were asked to indicate whether pictures were made with AI or hand-made by a human artist. Overall, several studies are showing that people struggle with identifying whether art was made by a human artist or by AI software. This suggests that people need more time to unlearn to get tricked because the general ability to distinguish between HA and AIA might improve with time and exposure.

There is evidence suggesting that people pick up on some sort of qualitative difference. Even though people are not able to consciously detect those differences and are not able to tell without practice whether a specific picture is made with AI, people might have the implicit capacity to distinguish between AIA and HA. As mentioned above, some research shows that people have difficulties in correctly identifying AIA. However, it may be the case that people simply need more exposure to AIA to learn to appreciate qualitative differences. The low accuracy identified by Gangadharbatla (2022) and Samo and Highhouse (2023) may simply be a result of AI generated images being a very novel phenomenon. Indeed, there is no research yet on whether it is possible to teach people the ability to distinguish between AIA and HA. Also, people seem to prefer HA over AIA. It was found that participants had a generally more positive aesthetic experience looking at art made by human artists and were more attracted to it (Samo & Highhouse, 2023). Lastly, participants reported they are more likely to hang HA in their homes rather than AIA. To conclude, people seem to enjoy looking at HA more compared to AIA even when they did not know whether a picture was AIA or HA. The current research aims at closing this gap by investigating whether a suitable learning paradigm will help people to be able to consciously distinguish between AIA and HA. So, people might unlearn to get tricked with the help of an effective learning paradigm.

A method with promising results already is spaced inductive learning. Inductive learning is the learning procedure that teaches to be able to generalize from relevant prior encounters. Spacing is the procedure of showing the stimuli (AIA and HA) interleaved. In the context of this study, this means that every other picture in the training condition will be an AIA artwork or rather HA artwork. This way, a HA stimulus always follows an AIA stimulus, vice versa. An inductive learning approach combined with spacing may be an effective way to teach people to differentiate between AIA and HA. Kang and Pashler (2012) state that an inductive learning approach is overall effective in the context of art. It benefits from additional spacing because seeing immediate contrast between pictures of two different artists enhances the learning procedure. Also, induction profits from spacing more compared to showing all visual stimuli altogether (i.e., massing; Kornell & Bjork, 2008). Kornell & Bjork (2008) show that this learning paradigm is effective in teaching people to distinguish between different artists' paintings. This leads to the assumption that an inductive learning approach, extended with spacing, may be effective in teaching people the ability to distinguish between AIA and HA.

Hypothesis 1: An inductive learning approach combined with spacing can teach people to better distinguish between AIA and HA.

There may also be individual differences in how effective this training method is for a participant. One such difference could be people's prior knowledge/interest. Interest in art may moderate the ability of a participant to effectively learn to distinguish between AIA and HA because more interested people might simply be more engaged and motivated in the learning process. Also, more art background knowledge might be helpful in the learning process because it might help register visual differences. In their study about memorizing written sentences, Shirey and Reynolds (1988) found that interesting sentences were much better recalled than sentences the participant did not assess as interesting. Therefore, interest may overall reinforce the learning process. This principle may be applicable in the context of learning how to distinguish between AIA and HA.

Hypothesis 2: People who are more interested in arts benefit more from the training compared to participants who are less interested in arts.

This study may contribute to an advance in the theoretical understanding of the perception of AIA in general. As stated above, there is not much research on AIA. Understanding whether it is possible to teach people to differentiate between AIA and HA gives insight into how the human mind perceives AI-generated pictures. Also, the outcome of this study may be informative about how advanced art-creating AI technology currently is. Depending on how well people can distinguish between AIA and HA after being taught the differences, art-creating software may be assessed as advanced or not. If unlearning to get tricked is indeed possible, people might feel less scared in their attitude toward the rather unknown world of AI. To conclude, this study may deepen the theoretical understanding of AI-generated artwork.

The Present Research

The main objective of this study is to test whether it is possible to teach people to identify the differences between AIA and HA through a spaced inductive learning paradigm. Due to the topic's novelty, there is not much research on it yet. This invites exploratory research. The secondary objective is to explore how individual differences moderate this ability. In addition, this study explores the accuracy of correctly identifying AIA for different types of paintings. The categories that will be used are portrait paintings, abstract paintings, and landscape paintings. Different types of paintings have different levels of complexity to it. Those differences in complexity might lead to certain categories to be more distinguishable than others.

To investigate the hypotheses, this study uses a quantitative research approach. Mainly, data on the outcome variable "AI and human-made art distinction accuracy" will be collected and analyzed to investigate whether there are differences between the groups. There will be two different groups in the experiment and each participant will be allocated to one of the groups randomly. The experimental group receives training in the form of spacing extended induction. The control group does not receive any kind of training and is asked to distinguish between AI paintings and human-made paintings without inductive learning.

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. The other participants were 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 on the main dependent variable (i.e. below 20 responses). 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 software package Midjourney (Holz, 2022) during 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, while some additional images were found from other websites. Again, 20 pictures from each of the previously mentioned categories were opted.

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 Art interest and affiliation, 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, we used a 7-item scale based on Specker and colleagues' (2020) Vienna Art Interest and Art Knowledge Questionnaire (VAIAK). The complete VAIAK can be found in Appendix B. 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 internal consistency of the artistic interest scale that was used in this study was good (α = 0.863).

AI Art affiliation

For the assessment of AI interest, we adapted the VAIAK scale (Specker et al., 2020) to ask about AI image generation instead. We adapted the items in such a way that the new scale measures self-reported AI interest using four items rated on a 7-point Likert scale (1 = *not at all*, 7 = *very much*) and three behavioral items regarding AI rated on a 7-point frequency scale (1 = *less than once per year*; 7 = *once per week or more often*). The self-reported AI interest 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 behavioral 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 interest scale that was used in this study was good (α = 0.801).

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 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, 2011). 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 human-art was captured with a single item: “Was this artwork made by a human or by Artificial Intelligence (AI)?”. There were two response options (“Human-made” 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 (1 = *Dislike a great deal,* 7 = *Like a great deal*) 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

To get an overview of this study's dataset, some descriptive statistics are presented first. Overall, Table 1 shows there are 47 valid data points for participants who did not receive training (condition 0) and 35 valid data points for participants who received training (condition 1). Valid data points do not include missing values on the dependent variable percentage of correct answers (indicated as 'AnswersCorrect%' in the tables). In total, 13 participants failed to respond to at least one of the artworks they were presented to and were thus removed from the dataset. Two other participants responded to one respectively seven artworks and were also removed from the dataset. The mean score on the dependent variable was 0.509 in the no-training condition and 0.573 in the training condition. The maximum possible score was 1.

Table 1

Descriptive Statistics

	AnswersCorrect%	
	1	0
Valid	35	47
Missing	0	0

Table 1

Descriptive Statistics

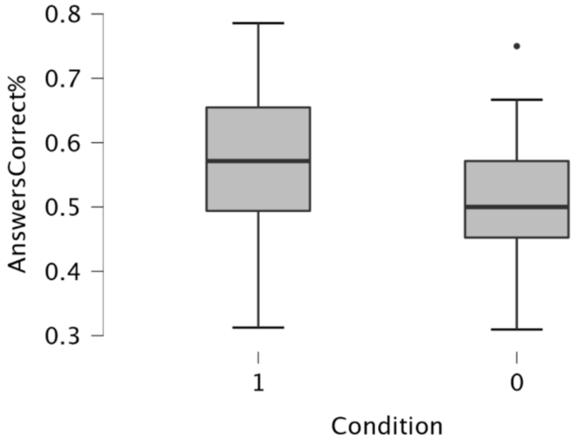
	AnswersCorrect%	
	1	0
Mean	0.573	0.509
Std. Deviation	0.102	0.094
Minimum	0.313	0.310
Maximum	0.786	0.750

Note. Excluded 1 rows from the analysis that correspond to the missing values of the split-by variable Condition

Figure 1 shows a boxplot that visualizes the differences between the two conditions. The values in the training condition have a slightly larger range than the values in the no-training condition. The maximum value in the no-training condition (0.75) is registered as an outlier in the boxplot.

Figure 1

Boxplot of both experimental conditions



To get an idea about how HA interest and interest in AIA influence the percentage of correct answers (‘AnswersCorrect%’), correlations are reported in Table 2. Neither HA interest nor AIA interest significantly correlates to the overall test score.

Table 2

Pearson’s Correlations

Variable		ArtInterest	Condition	AnswersCorrect%
1. ArtInterest	Pearson's r	—		
	p-value	—		
2. Condition	Pearson's r	-0.095	—	
	p-value	0.398	—	
3. AnswersCorrect%	Pearson's r	-0.063	0.170	—
	p-value	0.572	0.129	—

Hypothesis Testing

H1: An inductive learning approach combined with spacing can teach people to be able to distinguish between AIA and HA.

To test the first hypothesis a one-way ANCOVA was conducted. In this ANCOVA condition 0 (no training) and condition 1 (training) were compared on the dependent variable percentage of correct answers ('AnswersCorrect%'). The ANCOVA (Table 3) yields a significant result (p = 0.004). Thus, there seems to be a significant difference between the two experimental groups. Therefore, the data suggests that participants, who received training, were better at distinguishing between AIA and HA. The η_p^2 value indicates that this model explains 10.2% of the variance in the data. In conclusion, the data supports the first hypothesis.

Table 3

ANCOVA showing the effects of different training conditions and art interest on the percentage of correct answers

Cases	Sum of Squares	df	Mean Square	F	p	η^2_p
Condition	0.083	1	0.083	8.762	0.004	0.102
ArtInterest	0.004	1	0.004	0.422	0.518	0.005
Condition ✻ ArtInterest	0.007	1	0.007	0.690	0.409	0.009
Residuals	0.729	77	0.009			

Cases	Sum of Squares	df	Mean Square	F	p	η^2_p

Note. Type III Sum of Squares

H2: People who are more interested in arts benefit more from the training compared to participants who are less interested in arts.

To test the second hypothesis the interaction effect between art interest and the training condition was examined. The p-value of the interaction effect (p = 0.409) suggests that there is no significant interaction effect between art interest and the training condition of the participant. The corresponding effect size (η^2_p = 0.009) indicates adding the interaction effect to the ANCOVA model explains an additional 0.9% of the variance in the data. In conclusion, the data does not support the second hypothesis. People who are more interested in arts do not seem to benefit more from the training.

Exploratory Analyses

Difference between smartphone and desktop users

Overall, many participants completed the study on their phones. To scrutinize whether the device participants used made a difference in the accuracy of their responses, descriptives and the corresponding ANOVA were conducted. Table 4 shows, there is almost no difference in mean accuracy between the participants using a desktop ('AnswersCorrect%' = 0.536) and those using a smartphone ('AnswersCorrect%' = 0.537). The corresponding ANOVA (Table 5) is highly nonsignificant with a p-value of 0.955.

Table 4

Device specific descriptives

	AnswersCorrect%	
	Desktop	Smartphone
Valid	44	38
Missing	0	0
Mean	0.536	0.537
Std. Deviation	0.113	0.090
Minimum	0.310	0.317
Maximum	0.786	0.738

Note. Excluded 1 rows from the analysis that correspond to the missing values of the split-by variable Device

Table 5

ANOVA for device choice

Cases	Sum of Squares	df	Mean Square	F	p
Device	3.459×10^{-5}	1	3.459×10^{-5}	0.003	0.955
Residuals	0.849	80	0.011		

Cases	Sum of Squares	df	Mean Square	F	p

Note. Type III Sum of Squares

Artwork categories separated

While experimenting with the software and creating the stimuli for this experiment it was noticeable that Midjourney's (Holz, 2022) ability to create real-looking artwork differs between the categories. To get an overview of how the categories differ in terms of response accuracy, Table 6 was created to show descriptives for each artwork category. In most cases, the overall relative accuracy is higher when the participants receive training. The maximum accuracy was found for participants who received training and responded to AIA portraits. 73.6% of the responses were correct. The lowest accuracy was found for participants who did not receive training and assessed AIA abstracts. Only 38.9% of those responses were correct. The HA portrait category was the only category in which training related to less response accuracy. Participants, on average, performed worse on assessing HA portraits, when they received training.

Table 6

Descriptives for each artwork category

	AC_AiLandscape		AC_AiAbstract		AC_AiPortrait	
	1	0	1	0	1	0
Mean	0.649	0.534	0.456	0.389	0.736	0.537
95% CI Mean Upper	0.715	0.590	0.540	0.456	0.813	0.616
95% CI Mean Lower	0.583	0.479	0.372	0.322	0.658	0.458
Std. Deviation	0.193	0.190	0.245	0.229	0.226	0.271
Minimum	0.000	0.143	0.000	0.000	0.200	0.000
Maximum	1.000	1.000	1.000	1.000	1.000	1.000

	AC_RealLandscape		AC_RealAbstract		AC_RealPortrait	
	1	0	1	0	1	0
Mean	0.503	0.490	0.589	0.582	0.507	0.527
95% CI Mean Upper	0.568	0.547	0.662	0.650	0.574	0.590
95% CI Mean Lower	0.437	0.433	0.515	0.513	0.439	0.464

	AC_RealLandscape		AC_RealAbstract		AC_RealPortrait	
	1	0	1	0	1	0
Std. Deviation	0.190	0.194	0.213	0.233	0.197	0.214
Minimum	0.143	0.000	0.143	0.000	0.000	0.143
Maximum	0.857	0.857	1.000	1.000	0.857	1.000

Note. Excluded 1 rows from the analysis that correspond to the missing values of the split-by variable Condition

Discussion

This experiment examined whether teaching people to distinguish between AIA and HA through an inductive learning paradigm is possible. Also, differences between arts subcategories were assessed. Furthermore, it was tested whether art knowledge has an influence in the learning process. This experiment's sample included mostly first-year University of Groningen psychology students.

Results Summary

Hypothesis 1 stated that an inductive learning approach combined with spacing can teach people to be able to distinguish between AIA and HA. A significant effect was found to support the first hypothesis. According to the data that was analyzed in an ANCOVA, an inductive learning paradigm combined with spacing can teach people to distinguish between AIA and HA. An effect size of $\eta_p^2 = 0.1$ indicates a medium to large difference between the group that received training and those that did not. Those who received training correctly assessed whether a picture was AIA or HA more often. Thus, the data suggests a significant effect of the training.

Hypothesis 2 stated that people who are more interested in arts benefit more from the training compared to participants who are less interested in arts. The data did not support the hypothesis that people more interested in art benefit more from the training than those less interested in art. This suggests that the level of art interest in an individual does not have an influence in the effectiveness of the training.

Interestingly, there is no difference in response accuracy between participants who completed the study on a small phone screen compared to those who completed the study on a computer or laptop screen.

Furthermore, there are differences in accuracy between artwork categories. Some artwork categories were easier to distinguish than others. The AIA abstract paintings were the most difficult to be identified as AIA. Once training was received, the AI portraits were the easiest to be identified as AIA. Thus, overall, there are mixed results. The sample's limitations imply that the results need to be interpreted with caution and more research needs to be done on the topic to conclude certain effects.

Theoretical and Practical Implications

The major implication of this study is that spaced interleaved training has a significant effect in the context of teaching people to distinguish between AIA and HA. However, the accuracy in the training condition was still close to chance level (57.3%). Even though the low training volume of under 10 minutes in this study already yielded a significant difference between the conditions, it is not enough to reliably teach people to distinguish between AIA and HA. An extended and improved inductive training model might be useful to further improve the learning. Whether extended training is enough to teach people to reliably be able to distinguish between AIA and HA is a question this paper cannot answer.

This study found that, despite training, it is still very difficult for people to distinguish between AIA and HA, and protecting people from deception is important. Whether people might be able to improve their ability to become better judges is hypothetical. Depending on future development in the context of learning to distinguish between AIA and HA, strict policies that oblige AIA creators to label their art as artificially created might be necessary to protect the general population from deceit and fraud. Whether this is feasible, however, may be doubted.

Art education programs could integrate spaced inductive learning techniques to teach students to distinguish between AIA and HA. This may help students get a theoretical understanding of art that is not created by the human stroke of a brush. If more theoretical understanding is taught, this might open the possibility to consciously detect which visual differences individuals pick up on between AIA and HA. This, in turn, might be a better basis for a learning paradigm that might teach people to reliably distinguish between AIA and HA in the future.

Art dealers could also benefit from learning to distinguish between AIA and HA. Since it is already easy to artificially create art that looks almost indistinguishable from HA, people might abuse picture creation software to sell AIA as expensive HA. It is thus important for art buyers and sellers to be able to identify HA. This reduces the possibility for art dealers to become victims of fraud. Thus, art dealers could use a spaced inductive learning approach to become less prone to getting deceived.

Lastly, developers of AIA-creating software might use insights from studies like the current one to improve their artificial artwork creation. Table 7 shows there are differences in the ability of humans to detect AIA, depending on the artwork category. Whereas AI abstract artworks are already very hard to distinguish from HA, AI portraits seem to have room for improvement. These results also correspond to the personal impression the researchers of this paper had while creating the AIA. In conclusion, software developers that deal with AIA might investigate improving AI portrait creation, if they aim to create artwork that looks indistinguishable from HA.

Moreover, Table 6 shows that Midjourney's (Holz, 2022) ability to create artwork that looks like HA differs between art subcategories. According to the data, AI abstract art was more often identified as HA than not. This means that Midjourney (Holz, 2022) is especially good at creating abstract art that looks like HA. Moreover, participants who received training correctly identified AI portraits as AIA with a rather high accuracy (73.6%). This suggests it is easier for people to pick up on differences between AIA portraits and HA portraits. To conclude, Midjourney (Holz, 2022) differs in its ability to create HA-looking artwork, depending on the art subcategory.

After all, artificial Intelligence has large potential in artwork creation. Even though picture creating software is still new, the created artworks' quality is already astonishing. With time, picture creation will most likely improve, which makes it even easier to trick people with AIA. Even with an improved training paradigm, distinguishing AIA might become more difficult depending on how AI picture creation will develop.

Limitations

The sample has some clear limitations. Most of the participants completing this study were first-year Psychology students. This implies that the results cannot be generalized to the overall population and the population this study can be generalized to is rather specific. Furthermore, the sample size was low. The data of 82 participants was used for the final data analysis. Since most participants were students, the sample's age average can be assumed to be young. Salthouse (1994) suggests that younger people might benefit from learning more than older people. This means to limit the application of this study's results on a younger population. Also, it is justified to doubt the seriousness with which students conducted the study. Being part of those studies to collect a certain number of credits is mandatory for first-year Psychology students at the University of Groningen. This implies that some participants may have not taken this study seriously. In turn, this might have skewed the data, and the results may not reflect the actual population's ability to learn distinguishing between AIA and HA. Furthermore, many participants completed the experiment on a smartphone. A smartphone's small screen size might impair an individuals' ability to pick up differences between AIA and HA. An ANOVA was conducted on this and found no evidence for a difference between different device users.

On average, AI interest was very low in the sample. Almost all participants show low to neutral interest in AIA. Perhaps, participants could be better at identifying AIA when their theoretical knowledge about AIA is higher. People higher in AIA knowledge could benefit from being familiar with the theory behind how an AI software creates artwork from a prompt. By knowing the technical process behind artificial artwork creation, they might be more competent in identifying details in AIA that give away a picture is not hand-made.

Future Research

Improving the training could yield larger training effects. Since the training was rather short in this experiment, a larger training volume might yield better results. According to Smolen et al. (2016), longer intervals between the training might lead to better results. Also, participants might benefit from a higher training volume in general. Instead of presenting only a few paintings per category, the overall number of stimuli could be increased in the training condition. How far an improved training can take an individual's ability to distinguish AIA and HA is uncertain. However, it is unrealistic that even the most efficient training will be enough to reach a perfect identification accuracy. It is more realistic that improved training might increase an individual's ability to distinguish between AIA and HA but won't reach

100%. In conclusion, improved training that uses longer intervals between the training and a higher training volume in general might lead to better results.

Another reason why it is unlikely a perfect identification accuracy will be reached is improving software. Giving software developers time to develop AIA-creating software could impair peoples' ability to distinguish between AIA and HA altogether. Will learning still have the same effect in a few years when AI picture-creating software is improved? Future research might find an answer to this question.

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Appendix A

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.)?

Appendix B

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.)?