# Exploring the Impact of Inductive Learning on Recognition of AI-Generated Artworks

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## Abstract

The present study experimentally investigated the effect of inductive learning on people's ability to differentiate between AI-generated art and art painted by humans, whether the effects of inductive learning differs for different art styles, and whether prior art knowledge moderates the effect of inductive learning. Participants ($N$ = 82) were randomly assigned to an experimental group that received training exposing them to AI and non-AI generated art with interleaved presentation or to a control group that received no training. Participants also completed a questionnaire assessing their prior knowledge and interest in art. Overall, participants that received training were significantly better ($p$ = .004) at correctly classifying the AI and non-AI art. Significant effects of inductive learning were found for art in the styles landscape ($p$ = .028) and portrait ($p$ = .009), but not for abstract ($p$ = .180). Additionally, no moderation effect was found for prior art knowledge and interest ($p$ = .409). The found effect of inductive learning on AI art recognition has promising theoretical and practical implications. Because of the novelty of the topic, more research is needed to better understand the impact of inductive learning on people's ability to distinguish AI art from non-AI art.


*Keywords*: artificial intelligence, AI artwork, inductive learning

**Exploring the Impact of Inductive Learning on Recognition of AI-Generated Artworks**

In recent years, the creative field as a whole has witnessed a dramatic transformation with the emergence of Artificial Intelligence (AI) and machine learning. One of the most profound developments is the emergence of image generators that can create visual output by being fed text prompts or reference images. In the blink of an eye, generators like MidJourney and DALL-E can create images in styles ranging from photorealistic landscapes to abstract surrealisms, often indistinguishable from human made art (Samo & Highhouse, 2023). The rise of these revolutionary technologies has caused a paradigm shift in the creative field of visual arts, since it changed the creative process of many artists and the way we view their works. These recent advancements in machine learning and AI have sparked a surge in interest on how humans perceive and judge machine-made artwork. Since it is still an emerging field of research, due to the novelty of generative AI technology, there are many gaps in the literature.

One particular concern is about the dangers of AI-generated images. Given that it will only become more sophisticated, there is a concern that people for instance will fall for scams or political propaganda making use of AI-generated images. Precisely because the technology is so novel, it may be the case that people need to have more experience with it before they are better able to distinguish AI images from non-AI images. Or is it really the case that people will inevitably be fooled?

Some studies have been conducted on the capability of humans to distinguish between AI-generated and non-AI-generated artworks (artworks painted by humans) and their judgment of these artworks. Samo and Highhouse (2023) conducted a study where they exposed participants to both AI artworks and non-AI artworks and were then asked to identify the source of the artwork. Subsequently, the participants were asked to give their aesthetic judgment of the artworks. The study found that the participants were unable to correctly differentiate between the AI images and the non-AI images. However, they did find that the aesthetic judgment by the participants differed between AI made and non-AI made art. The study finds that individuals perceive and evaluate human-generated artworks as possessing greater authenticity and creativity compared to machine-generated ones. Participants tend to attribute higher artistic value to non-AI art, emphasizing qualities such as originality, emotional depth, and conceptual richness. In contrast, AI-generated artworks are often perceived as lacking in these qualities and are evaluated less favorably in terms of aesthetic appeal and artistic merit. This is an interesting finding, since the participants apparently do not know what the difference is between the stimuli as they were unable to tell AI images and non-AI images apart, but seemingly unconscious do feel there to be a difference in aesthetic quality between the AI-generated artworks and non-AI-generated artworks. Similar results were found in a study by Gangadharbatla (2021) which also featured a design where participants had to identify whether art was non-AI-generated or AI-generated. The participants in this study were also unable to identify the source of the artworks. Chamberlain et al. (2018) additionally found that the participants of their study, examining the ability to differentiate between AI artworks and non-AI artworks, were also unable to do so. However, Chamberlain et al. (2018) found evidence as well for an implicit bias for human artwork in regard to its aesthetic quality.

These results seem to indicate that the participants of the aforementioned studies implicitly picked up on inherent qualities of the non-AI-generated artworks that are lacking in AI-generated art. These implicit differences between the aesthetic judgements of the artworks, suggest that people are indeed able to pick up on some qualitative differences between AI art and non-AI art. Since AI is such novel technology – and the average person likely has not much experience with it - it may simply be the case that they need to get more exposure to AI generated images and might benefit from training in detecting differences between AI and non-AI art. If true, this ability would hold significant importance in an era increasingly defined by the integration of artificial intelligence into various facets of society (Gangadharbatla, 2021).

One way humans learn to differentiate between categories in the real world is through inductive learning. Inductive learning happens through the observation of exemplars, and based on these observations the learner recognizes patterns or regularities that are indicative of broader categories (Kornell & Bjork, 2008). Inductive learning happens constantly, for instance in learning social cues through interactions with others or learning generalized cooking techniques by following recipes. Inductive learning has already been shown to improve accuracy in the context of judging pieces of art. Kornell and Bjork (2008) tested the effect of spacing versus massing of exemplars on inductive learning. The participants were exposed to paintings by different artists of a similar art style. Participants in the massing condition were shown multiple artworks by one artist in one block and then multiple artworks by another artist in another block, continuing this until the participant had seen all the artworks. The artworks were accompanied by the corresponding artist’s name. Participants in the spacing condition received the artworks by different artists in an alternating fashion, first seeing an artwork by a certain artist accompanied by the artist's name and then seeing an artwork by a different artist accompanied by the artist’s name, repeating this until they saw all the artworks. After the learning phase the participants received a test where they were shown novel artworks by artists from the learning phase and were asked to correctly identify by whom the artworks were made. Kornell and Bjork (2008) found that participants in the spaced condition, where the different artists were interleaved, did significantly better in recognizing the artist by art style. From the results of this study it was not yet clear whether the beneficial effects of spacing was due to temporal spacing between the artworks or due to the interleaving of the artworks. Kang and Pashler (2011) conducted a study to investigate the effects of temporal spacing and interleaving on inductive learning. In their study they replicated the finding that spacing is superior to massing when it comes to inductive learning. Additionally, they found that the benefit of spacing was due to the interleaving of artists and not because of the temporal spacing of the artists. Kang and Pashler (2011) argue that the juxtaposition of artists enhances discrimination learning, because the participant is better able to compare similar stimuli and find differences. They add that the discriminative contrast due to interleaving might only promote inductive learning when the categories are very similar. Thus, interleaved inductive learning may be the most promising option when it comes to teaching people to learn the difference between AI art and non-AI art. The studies by Samo and Highhouse (2023), Gangadharbatla (2021) and Chamberlain et al. (2018) demonstrated that the participants of their studies were not able to differentiate between the artworks by AI and non-AI, but that they implicitly picked up on some differences of aesthetic qualities. The aforementioned studies did not contain a training phase and the participants were asked to differentiate between categories without prior exposure. Incorporating interleaved inductive learning before image classification might improve the participant's ability to distinguish between AI and non-AI made artworks.

Hypothesis 1: People exposed to an interleaved training condition will perform better in correctly classifying AI artworks and non-AI artworks than those that receive no training.

Not all people will benefit from inductive learning in the same way. There are multiple candidates for individual differences that could make training more/less effective. One such factor is whether the individual has substantial prior experience or knowledge in the art domain. People with experience in the artistic domain and with better knowledge of art think and feel different about art and are better at recognizing structural features of artworks (Silvia, 2006). This difference in perception of art in persons with more art knowledge will likely enable them to have a more complex assessment of the aesthetic qualities and details of an artwork and therefore will be better at picking up on (implicit) differences between the AI art and non-AI art.

Hypothesis 2: People with more prior interest in art and knowledge of art will benefit more from the interleaved training and will perform better at the classification of AI artworks and non-AI artworks than those with less or no interest in and knowledge of art, because prior art interest and knowledge will have a moderating effect on the relationship between the interleaved training condition and the performance on the artwork classification.

Furthermore, this study is going to explore whether different art styles benefit from inductive learning in different ways. The training effect is going to be tested on artworks from three different art styles: landscape, portrait and abstract.

The current study aims at testing these hypotheses through an online study in which art knowledge and interest will be measured and participants will either receive an inductive learning training condition or receive no training. Subsequently, the participants will be asked to complete a test phase assessing their ability to differentiate between AI and non-AI art in the categories ‘landscape’, ‘portrait’ and ‘abstract’. The effect of training and art interest will be analyzed based on their scores on the art classification test and their answers on the art interest scale.

## Methods

### Participants

A part of the sample (*N* = 100) contained participants collected via the SONA-systems platform for first-year psychology students at the University of Groningen, who received course credits for their participation (*n* = 35). The other participants were recruited through convenience sampling based on the social network of the authors (*n* = 65). Data cleaning excluded 18 participants who gave insufficient answers on the main dependent variable (i.e. below 20 items answered). The final sample used in this study therefore consisted of 82 participants. No demographic data was recorded. The data was collected between the 4th of May and the 20th of May 2024.

**Design of the Stimuli**

A set of 120 images was compiled, consisting of 60 AI-generated artworks and 60 non-AI artworks. The AI-generated artworks were created with the software package MidJourney (MidJourney Inc., 2023) 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 can be found in the Appendix. 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 non-AI 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, we opted for 20 pictures from each of the previously mentioned categories, resulting in a total of 60 non-AI images.

**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 Knowledge Questionnaire (VAIAK; Specker et al., 2020).

### *Art Interest and Art Knowledge*

For the assessment of art interest, we used a 7-point Likert 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 internal consistency of the artistic interest scale that was used in this study was good ($\alpha = 0.863$).

### *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 five items rated on a 7-point Likert scale (1 = *not at all*, 7 = *very much*) and two 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: "How often do you look specifically for AI artworks?" 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 ($\alpha = 0.801$).

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 in the training phase, 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 & Pashler, 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 non-AI-art was captured with a single item: “Was this artwork painted by a human or Artificial Intelligence (AI) generated?”. There were two response options (“Painted by a human” 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 artwork; a 7-point Likert-scale was applied (1 = *not at all*, 7 = *very much*). 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 were finished with the test, they had the opportunity 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.

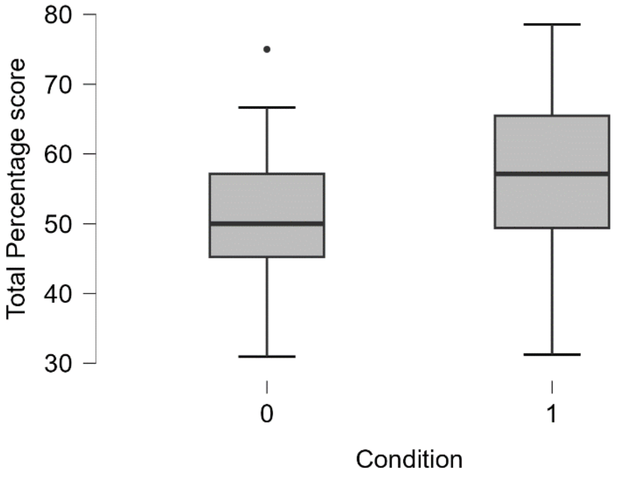
## Results

### Descriptive Statistics

To assess whether training through inductive learning improved image classification, performance was operationalized in the amount of correctly identified artworks as AI or non-AI. Since not all the participants completed the total of 42 image classifications, a percentage score was calculated instead of the absolute score in order to accurately compare the scores between participants. The percentage score was calculated by dividing the amount of correct answers by the total amount answered in the image classification part of the study. This yielded an average of 50.9% (*SD* = 9.4) correct answers for the control group and an average of 57.3% (*SD* = 10.2) correct answers for the experimental group (see Table 1 and Figure 1). The average percentage scores per art style for the group that received no training were 51.1% (*SD* = 12.5) for landscape, 53.2% (*SD* = 16.2) for portrait and 48.4% (*SD* = 12.4) for abstract (Table 2). The average percentage scores per art style for the group that received training were 57.6% (*SD* = 13.5) for landscape, 62.2% (*SD* = 13.4) for portrait and 52.4% (*SD* = 14.0) for abstract (see Table 2).

**Figure 1**

*Average Total Percentage Scores for the Control Group (0) and the Experimental Group (1)*



**Hypothesis Testing**

A one-way ANOVA was used to test the hypothesis that people exposed to an interleaved training condition will perform better in correctly classifying AI artworks and non-AI artworks than those that receive no training (H1). The one-way ANOVA using the total percentage scores as dependent variable and the experimental condition of the participant as fixed factor, demonstrated that the effect of training was significant on the performance on image classification, $F(1, 80) = 8.85$, $p = .004$ (see Table 3). Thus, this analysis supports the primary hypothesis that training through inductive learning can improve a person's ability to differentiate between AI and non-AI made artworks.

To test hypothesis 2 – that the effect of the interleaved training on image classification performance will be stronger for people with more art knowledge and interest, through a moderation effect of prior art knowledge and interest - an ANCOVA was used. The ANCOVA used the total percentage scores on the image classification as dependent variable, the experimental condition of the participant as fixed factor, the total score on the art knowledge and interest scale as covariate, and it included the interaction effect between the total score on the art knowledge and interest scale and the experimental condition, in order to test for an interaction effect between the experimental condition and prior art knowledge and interest. The ANCOVA demonstrated that there was no significant moderating effect of prior art knowledge and interest on the relationship between the presence of training and the percentage score on image classification, $F(1, 77) = 0.69$, $p = .409$ (see Table 4). Thus hypothesis 2 was not supported, prior art knowledge and interest has no significant moderating effect on the relationship between training through inductive learning and the score on image classification.

## Exploration of Differences Between Art Styles

For each of the three art styles (landscape, portrait and abstract) an ANOVA was performed to explore possible differences of the effect of inductive learning for the different art styles. The percentage scores on the classification of the artworks per art style were used as dependent variable, with the experimental condition as fixed factor. The ANOVA performed for the art style ‘landscape’ demonstrated that the effect of training was significant on the performance on image classification, $F(1, 80) = 5.038$, $p = .028$ (see Table 5). The ANOVA performed for the art style ‘portrait’ demonstrated that the effect of training was significant on the performance on image classification, $F(1, 80) = 7.137$, $p = .009$ (see Table 6). Although the participants that received training did perform slightly better at correctly classifying the abstract artworks, the ANOVA performed for the art style ‘abstract’ demonstrated that the effect of training was not significant on the performance on image classification, $F(1, 80) = 1.831$, $p = .180$ (see Table 7). Thus, training through inductive learning has different effects on image classification performance depending on the art style. While there was a significant effect of training for the art styles ‘landscape’ and ‘portrait’, no significant effect of training was found for the art style ‘abstract’.

# Discussion

This study investigated whether training through inductive learning, making use of interleaved stimuli presentation, improved a person’s ability to accurately classify between AI-made and non-AI-made artworks. It also investigated if prior art knowledge and interest had a moderating effect on the relationship between the inductive learning training and the performance on artwork classification. Furthermore, it was explored if there were different effects of inductive learning for different art styles (landscape, portrait and abstract).

The results of the study are in line with the main hypothesis, that training through inductive learning making use of interleaved artwork presentation, improves the performance on AI and non-AI artwork classification, since the participants in the training condition were significantly better at distinguishing AI and non-AI artworks than those in the control group. The results showed that without training the participants performed around chance level when classifying the artworks, replicating the results found by Samo and Highhouse (2023), Gangadharbatla (2021) and Chamberlain et al. (2018). On the other hand, the participants that received training significantly improved their performance by more than 7% on the artwork classification test. This implies that the participants were able to pick up on differences between the AI art and the non-AI art through inductive learning. These results show that the effect of interleaving artworks on inductive learning, found by Kornell and Bjork (2008) and Kang and Pashler (2011), translates to learning to recognize the source of an artwork as AI or not. This significant effect of training on AI artwork recognition was found after a training phase with a duration of merely 10 minutes. The aforementioned results suggest that exposure leads to better recognition of AI artwork and that people just need more experience with AI-generated art to improve their ability to distinguish it from non-AI-generated art. Perhaps people will not be inevitably fooled by AI just yet.

The results of the study found no evidence for the secondary hypothesis that prior art knowledge and interest has a moderating effect on the relationship between training through inductive learning and image classification performance. Meaning that the participants with higher scores on the VAIAK (Specker et al., 2020) questionnaire did not significantly benefit more from the inductive training than those with lower scores. Therefore, the participants of this study did not benefit from better knowledge of art and experience in the artistic domain during the training phase, when it came to recognizing inherent structural features or aesthetic qualities of AI artwork, in order to differentiate them from non-AI artwork.

Regarding further explanatory analyses, the study found differences in the effect of training through inductive learning for the different art styles. Participants that received training were significantly better at correctly classifying the artworks in the art styles landscape and portrait than the participants that did not receive training, but this significant effect of training was not found for the artworks in the abstract art style. This difference in the effect of training for abstract art might be explained by the possibility that AI is better at generating abstract art indistinguishable from non-AI abstract art, than it is in the styles landscape and portrait. Another reason for the difference in training effects could be that landscape and portrait artworks more closely resemble reality. This familiarity might make it easier for people to spot irregularities in AI-generated representations of these styles. In contrast, abstract art does not directly depict real life, making it impossible to compare it to real-world equivalents. These findings suggest that recognizing AI art through inductive learning is effective only for art that mimics reality, indicating that the benefits of such training are limited to certain art styles.

**Strengths, Limitations, and Future Research**

One of the strengths of this study is its relevant and innovative subject matter. Enhancing theoretical and practical knowledge of such a novel concept as AI recognition by humans is undoubtedly a valuable endeavor in today's world. This study demonstrated that inductive learning is applicable on recognition of AI artwork and this finding is a valuable contribution to the current literature. Additionally, the discovered inductive training effect offers practical applications for developing training and education programs on AI art recognition, which will surely be useful in current times.

Another strength of the study is the quality of the selected stimuli, particularly in ensuring that the AI-generated images were not easily identifiable as such. This is demonstrated by the fact that the participants of this study that received no training were seemingly unable to tell the AI artworks apart from the non-AI artworks, as they performed at chance level on the image classification test.

A limitation of this study is the small sample size (*N*=82). The nonsignificant result found for the analysis of the possible moderating effect of art knowledge and interest on the relationship between training and the performance on image classification, might be due to insufficient power, as the result of too small of a sample size. It is noteworthy that despite the small sample size, significant results were found supporting the main hypothesis on the effect of training trough inductive learning. In future research on this topic, a larger sample size is warranted to ensure sufficient power.

Another limitation is the composition of the participant sample. The participants were recruited through convenience sampling of first-year psychology students at the University of Groningen and through the network of the researchers. This way of recruiting participants may have resulted in bias in the participant sample and reduces the external validity of the results. It is possible e.g., that because of the homogeneity of the sample, people with prior art knowledge and interest were underrepresented in the sample. It might be the case that a possible moderation effect of prior art knowledge on the relationship between inductive training and test performance could not be measured in this sample, because of the lack of realistic variability in the amount of prior art knowledge and interest among the participants. In future research, participant recruitment through probability sampling is advised, to safeguard the external validity and the generalizability of the results. Another way to accurately test the possible moderator effect of prior art knowledge on the relationship between training and image classification performance, would be to recruit a sample of participants who are/were active in the artistic domain and compare this sample with a probability sample from the general public. This way, it is certain that the sample contains participants with high scores on art knowledge and interest, and the possible moderator effect is easier to detect if present.

A different factor that might have contributed to a bias in the research is the way the AI artworks were generated and selected. The AI artworks were generated through text prompts devised by the researchers and subsequently a selection from these generated artworks was made by them as well. One could argue that the participants possibly picked up on characteristics of the AI artworks selected for by the researchers, instead of characteristics inherent to AI-generated images. Thus, the selection process of the AI artworks might have resulted in a bias in the utilized stimuli in the study. In future research, a more objective way of generating and selecting AI stimuli is favorable. This can be achieved by preselecting text prompts and, as a form of quality control, using the resulting generated images in a pre-test. In this pre-test, participants without prior training would classify the images as either AI-generated or not. Only the AI-generated artworks that were correctly identified about half of the time would be selected for the study, to ensure the AI-generated images are not easily identifiable as such, at first glance.

Furthermore, this study found that through inductive learning participants were able to pick up on differences between AI and non-AI artworks, but the current study did not investigate what those recognized differences by the participants were. In a follow-up study it would be valuable to assess whether participants are able to articulate what makes them classify an artwork as AI or non-AI. Explicit verbal feedback from participants about their assessments of the artworks could help explain why training had a significant effect on portraits and landscapes, but not on abstract art. This feedback might reveal the defining characteristics that AI-generated abstract art lacks, which are present in AI-generated portraits and landscapes. Above all, knowledge on what features and characteristics of AI artwork makes them detectable as such, makes development of a training in AI detection feasible. Training in AI detection could reduce the risk of people falling for scams or political propaganda exploiting image generating AI.

An additional factor to keep in mind is the unprecedented pace at which AI is evolving. This rapid evolution poses a challenge for AI research as the speed of technological advancements often outpaces the researchers ability to fully comprehend and analyze the current state of AI. The dynamic nature of AI development means that research can quickly become outdated. It’s very plausible that after the completion of this study, the ability of AI to generate images further improved, altering the effects of training through inductive learning on AI image detection found in this current study. However, this dynamic nature also makes research on AI exciting and innovative. What makes the results of the current study exciting, is that we showed that without prior exposure or training, people as of present seem unable to tell AI and non-AI artworks apart, but incorporating an uncomplicated one-time training, already significantly improved their performance. This is promising for future research on human ability to detect AI generated images and possible development of training and education on this topic. The literature on AI image recognition by humans is still in its infancy and there are numerous opportunities for future research in this area. As previously mentioned, it's valuable to study both the aspects of AI art that enable recognition through inductive learning and how this inductive learning can be applied to different art styles, contexts, and populations. The findings of such research could significantly benefit society by maximizing the positive aspects of image-generating AI while mitigating its negative implications.

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# Tables

**Table 1**

**Descriptive Statistics for the Control group (0) and the Experimental Group (1)**

| | Total Percentage score | |
|---|---|---|
| | **0** | **1** |
| Valid | 47 | 35 |
| Missing | 3 | 10 |
| Mean | 50.854 | 57.348 |
| Std. Deviation | 9.409 | 10.249 |
| Minimum | 30.952 | 31.250 |
| Maximum | 75.000 | 78.571 |

*Note.* Excluded 3 rows from the analysis that correspond to the missing values of the split-by variable Condition

**Table 2**

**Descriptive Statistics for the Control group (0) and the Experimental Group (1)**

| | Total Percentage score Abstract | | Total Percentage score Landscape | | Total Percentage score Portrait | |
|---|---|---|---|---|---|---|
| | **0** | **1** | **0** | **1** | **0** | **1** |
| Valid | 47 | 35 | 47 | 35 | 47 | 35 |
| Missing | 3 | 10 | 3 | 10 | 3 | 10 |
| Mean | 48.397 | 52.356 | 51.094 | 57.567 | 53.158 | 62.163 |
| Std. Deviation | 12.409 | 13.989 | 12.462 | 13.508 | 16.242 | 13.395 |
| Minimum | 28.571 | 18.182 | 28.571 | 25.000 | 21.429 | 35.714 |
| Maximum | 75.000 | 85.714 | 83.333 | 85.714 | 85.714 | 92.857 |

*Note.* Excluded 3 rows from the analysis that correspond to the missing values of the split-by variable Condition

**Table 3**

**ANOVA - Total Percentage score**

| Cases | Sum of Squares | df | Mean Square | F | p |
|---|---|---|---|---|---|
| Condition | 845.860 | 1 | 845.860 | 8.853 | 0.004 |
| Residuals | 7643.784 | 80 | 95.547 | | |

*Note.* Type III Sum of Squares

**Table 4**

**ANCOVA - Total Percentage score**

| Cases | Sum of Squares | df | Mean Square | F | p |
|---|---|---|---|---|---|
| Condition | 829.372 | 1 | 829.372 | 8.762 | 0.004 |
| ArtknowledgeTotal | 39.991 | 1 | 39.991 | 0.422 | 0.518 |
| Condition ✻ ArtknowledgeTotal | 65.303 | 1 | 65.303 | 0.690 | 0.409 |
| Residuals | 7288.409 | 77 | 94.655 | | |

*Note.* Type III Sum of Squares

**Table 5**

**ANOVA - Total Percentage score Landscape**

| Cases | Sum of Squares | df | Mean Square | F | p |
|---|---|---|---|---|---|
| Condition | 840.599 | 1 | 840.599 | 5.038 | 0.028 |
| Residuals | 13348.243 | 80 | 166.853 | | |

*Note.* Type III Sum of Squares

**Table 6**

**ANOVA - Total Percentage score Portrait**

| Cases | Sum of Squares | df | Mean Square | F | p |
|---|---|---|---|---|---|
| Condition | 1626.747 | 1 | 1626.747 | 7.137 | 0.009 |
| Residuals | 18235.413 | 80 | 227.943 | | |

*Note.* Type III Sum of Squares

**Table 7**

**ANOVA - Total Percentage score Abstract**

| Cases | Sum of Squares | df | Mean Square | F | p |
|---|---|---|---|---|---|
| Condition | 314.493 | 1 | 314.493 | 1.831 | 0.180 |
| Residuals | 13737.102 | 80 | 171.714 | | |

*Note.* Type III 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 strength 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

All about you- Vicky Barranguet

Coachella Valley- Jeffrey Tover

Cosmos, Inside- Naomi Yuki

Zebras - Victor Vasarely

Electric Prisms- Sonia Delaunay

Los Angeles - Jeffery Tover

Night Ride- Jeffrey Tover

Nothing held back- Vicky Barranguet

Roads not taken- Vicky Barranguet

Turquoise Moon- Paul Franklin

Dynamic Suprematism- Kazimir Malevich

***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

Watermolen- Meindert Hobbema

Waterfall at Mont-Dore- Achille Etna Michallon

Sunset on the Normandy Coast- Eugene Isabey

On the Quirinal Hill- Simon Denis

Savanna- R.S. Duncan

Richmond Castle, Yorkshire - Philip Wilson Steer

Cherry Blossom - Eric Hanson

The Mascot - Simon Stalenhag

Sunrise- Claude Lorrain

Viaduct of the Arc River Valley- Paul Cezanne

***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 Art Knowledge Questionnaire (VAIAK; Specker et al., 2020)**

1. I like to talk about art with others. .831

2. I'm interested in art. .842

3. I'm always looking for new artistic impressions and experiences. .797

4. In everyday life I routinely see art objects that fascinate me. .703

5. How often do you visit art museums and/or galleries? .749

6. How often do you read books, magazines or catalogs about art? .754

7. How often do you look at images of artworks (catalogs, internet, etc.)? .735

8. How often do you paint/draw/make sculptures, or any other type of visual art?

**VAIAK (Specker et al., 2020), Adapted AI Scale**

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

2. I’m interested in AI art.

3. I frequently spend time gathering more knowledge about AI art.

4. In everyday life I routinely encounter AI art that fascinates me.

5. I enjoy using AI tools to generate art.

6. I am fascinated by the recent developments in AI art.

7. How often do you use AI tools to generate art?

8. How often do you look specifically for AI artworks?