Is it AI? Can people learn to spot the difference between real photographs and AI-generated photorealistic images?

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Abstract

Being exposed to Artificial Intelligence (AI) generated photorealistic images is no longer a rarity. Due to the rapid advancement of AI, it is also becoming increasingly harder to distinguish between what is real and what is AI. The present study investigates the effect of an interleaved inductive learning training on people's ability to spot the difference between real photography and AI-generated photorealistic images. Participants (N = 192) were randomly assigned to either receive training or no training, which was followed by questionnaires and the test phase of the study. The training shows virtually no effect on the overall accuracy scores. However, an opposite effect pattern appears when we look at the image categories separately. Namely, that 'real photography' accuracy scores are lower for participants in the training condition, and accuracy scores for 'AI generated' are higher for participants in the training condition. Higher AI-related anxiety scores show a positive relationship with the accuracy score for the 'AI generated' category, while having received both training and having higher anxiety scores has a negative impact. Interestingly, there is no significant effect for the 'real photography' category. Our findings also show that, on average, women tend to be better than men at accurately distinguishing between categories. Due to the novelty of the topic, more research is needed to attain a more thorough understanding of what impacts and is needed for AI media literacy, and whether it is even possible to still distinguish between AI-generated images and real photography.

Keywords: Artificial Intelligence, AI, AI-generated photorealistic images, photography, interleaved inductive learning, AI media literacy, AI-related anxiety

Is it AI? Can people learn to spot the difference between real photographs and AI-generated photorealistic images?

What comes to mind when you think of AI-generated photorealistic output? Hands that have too many fingers or not enough? Your family member sending you an image of a cute kitten that is cuddling with a human baby, both of which look clearly AI-generated, but not to them? Perhaps a video of a politician saying outrageous things, but their mouth movement does not match up with the audio? Some of those might be obvious to you, but can you say with absolute certainty that you always spot AI-generated content? If you use Apps to communicate with friends and family or spend your time on social media platforms, it is very likely that by now you have come across AI-generated images or videos, possibly without even being aware of it. So, how can you tell if something is AI-generated, and should you even care?

Undoubtedly, AI image-generating programs are evolving rapidly, creating more photorealistic-looking output with every upgraded version. As AI output becomes harder to distinguish from reality and we are slowly catching up to AI's negative impacts, AI media literacy only grows in importance. Ethical issues such as algorithmic bias (Buolamwini & Gebru, 2018), and the wider societal impact of AI, including AI's carbon footprint (George, A. et al., 2023), have received increased attention as a result. Yet, critical voices tend to be disregarded by the respective companies, such as Timnit Gebru who was Google's co-lead of the ethical AI team until 2020 when she gained media attention after co-authoring a paper[1] which ultimately led to her forced departure from Google, giving us one example how tech companies handle transparent research regarding the ethical implications of AI (Harris, 2023).

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[1] Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? *In Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (FAccT '21).*, 610–623. https://doi.org/10.1145/3442188.3445922

Further highlighting the importance of AI media literacy, the International Centre for Counter-Terrorism (ICCT) published a Policy Brief in December 2023, titled ‘The Weaponisation of Deepfakes Digital Deception by the Far-Right’ (Busch et al., 2023). Besides the potential for political propaganda (Hartmann & Giles, 2020; Karnouskos, 2020), famous people, and especially women, are oftentimes targeted for nefarious purposes. Ajder and colleagues (2019) conducted a study concerning Deepfake detection and evaluation. Revealing that 96% of detected Deepfakes were of explicit nature, which constituted of 100% women, while out of the 4% that were non-explicit 61% represented men. A more recent news article reports that 1 in 6 US Congresswomen are targeted by AI-generated sexually explicit Deepfakes (Rodriguez et al., 2024). These findings give emphasis to the necessity and importance of AI media literacy, including understanding the wider implications of AI and learning how to spot the differences between what is ‘real’ and what is AI-generated.

The need for AI media literacy has also become highly relevant for artists, as their livelihood has been affected by the unregulated development and use of generative AI tools. Legal actions regarding copyright infringement have been initiated by authors (The Authors Guild, 2023), photographers (Jingna, 2024) and painters (Chayka, 2023). Artists have also denounced ‘AI art only’ auctions (Milmo, 2025) that legitimise the use of generative AI models, such as Midjourney[2], that have been trained on stolen artworks (Jingna, 2025). At the same time, unsolicited AI integrations are introduced into everyday life; from AI being automatically used during Google searches (Schwartz, 2024), to Zalando’s AI imagery (Reid, 2025), to H&M’s ‘AI models’ (Bain, 2025). While we are aware of AI being used in the first instance, it might not be so straightforward when looking at advertisement campaigns from

[2] Midjourney was the image generating AI model chosen to generate the images for our study. Midjourney supposedly has a ban on NSFW content as stated in their Midjourney Community Guidelines (Midjourney, n.d.). However, during our image generation phase, we came across unprompted explicit images depicting women.

clothing retailers. Will we be able to distinguish between H&M's 'real' models and its 'AI models'? Is it possible to train ourselves to spot AI-generated images?

Assuming that it is still possible to pick up subtle differences and to distinguish between 'real' and 'AI generated' images, individuals should be able to learn to spot these differences essentially through exposure. One particularly successful approach is inductive learning, which is a way of learning that is facilitated by the observation of new material. Previous research by Kang and Pashler (2011) and Kornell and Bjork (2008) demonstrated that inductive learning is an effective strategy for distinguishing subtle differences between different painters and their accompanying painting styles. Both studies revealed that inductive learning benefits from the interleaving of stimuli (spacing), meaning exposure to intermixed artworks from different painters led to better accuracy scores compared to the other condition that exposed the artworks in sequential order (massing). Verkoeijen and Bouwmeester (2014) successfully replicated Kornell and Bjork's (2008) findings, contributing further evidence that when it comes to inductive learning, spacing is more beneficial than massing. The same principle that worked for different styles of painters should therefore translate to AI media literacy. By interleaving the two image categories, their distinctive contrast should become more prevalent, helping people to spot the subtle differences between real photography and AI-generated photorealistic images.

This leads to the first prediction:

H1: People who undergo an interleaved inductive learning training will become better at distinguishing AI-generated images in comparison to people who receive no training.

Given that the inductive learning effect relies on spotting subtle differences, pattern recognition plays a central role. This is because throughout inductive learning training people already inductively infer that the perceived differences signal separate categories. Research on anxiety has found that anxious individuals tend to demonstrate threat-related attentional bias and stronger pattern recognition regarding those threats (Bar-Haim, et al., 2007), as well as that general emotionality of the stimuli matters, and anxious individuals show more vigilance during early processing stages of the stimuli regardless of whether the scene presented was positive or negative (Calvo & Avero, 2005). Following the same logic, people who exhibit higher levels of AI-related anxiety may also benefit more from the inductive learning training because they tend to be more prone to focus their attention on potential threats, and they tend to be more proficient in pattern recognition, compared to non-anxious individuals.

We predict the following:

H2: The benefit of training interacts with AI-related anxiety. People who exhibit higher levels of AI-related anxiety will benefit more from training, compared to participants who score low on AI anxiety.

Furthermore, cumulative research shows that women predominantly represent anxiety disorders compared to men (McLean et al., 2011; Pesce, et al., 2015; Remes et al., 2016). This insight, in addition to negative implications of AI models, such as racial and gender biases (Buolamwini & Gebru, 2018), Deepfakes weaponisation (Ajder et al., 2019; Busch et al., 2023; Rodriguez et al., 2024), which primarily affects women in harmful ways, ought to follow that women will perceive AI to be a greater threat than men. Indeed, a recent study conducted by Russo and colleagues (2025) revealed significant gender differences on several AI-related dimensions, such as AI anxiety, with women displaying higher levels of anxiety.

Leading to the following prediction:

H3: Women will score higher on the AI-related anxiety scales compared to men.

In addition, research has revealed that there are gender differences in regard to learning. Such as that women tend to perform better on processing speed tasks, that is how quickly and accurately one responds to stimuli and processes information (Camarata & Woodcock, 2006), and women seem to generally have an advantage when it comes to memory related tasks, such as facial recognition, which is connected to women's increased scanning behaviour when it comes to encoding stimuli (Heisz et al., 2013). Given that inductive learning trainings are usually composed of the same content for any gender group, women might be more efficient learners, as they tend to process stimuli faster and thus benefit more from the same learning material. This should put women at an advantage when it comes to spotting subtle differences when exposed to stimuli. Another way in which women might be more attentive to AI-related stimuli is by stereotype threat. While research has shown that women are often negatively impacted in their performance once they are confronted with situations that activate or confirm negative stereotypes about their gender group (Boucher et al., 2015; Shapiro et al., 2012), more recent research found evidence that there are also positive effects. Cortland and Kinias (2023) observed that women in workplace settings displayed increased motivation to mitigate gender inequality. Arguably, perceived workplace gender inequality should translate to perceived AI-related gender inequality, increasing the possibility that women become more motivated to want to accurately detect AI-generated content.

Leading to the prediction:

H4: Women will be better at distinguishing between image categories compared to men.

Methods

Participants

An initial $N = 222$ participants were recruited for the study. The participants represent a convenience and snowball sample, made up of participants recruited both through the University of Groningen's SONA platform ($n = 188$) and privately by the research team, the latter of whom were asked to refer additional participants ($n = 34$). Participants from the SONA pool participated for course credit, while those recruited privately voluntarily took part in the study and received no compensation. Seventeen participants were excluded due to incomplete responses, 9 participants due to failing the attentions checks, 2 for missing more than one item per subcategory during the test phase, another participant for straightlining the highest response options (incl. on reverse coded items), also showing up as an outlier (Cook's distance > 5), for a final total of $N = 193$. Of the final sample, 70.98% were female ($n = 137$), 28.49% were male ($n = 55$), and 0.51% were non-binary ($n = 1$). For the gender related analysis, one participant was excluded due to n=1 for the third gender category not being a representative sample. Participants had to be at least 16 years old. Data collection for the study ran during the month of April 2025.

Materials and stimuli

The study was conducted as an online experiment hosted on Qualtrics. After giving informed, active consent, all participants were first asked to fill in a number of scales and items.

Anxiety related to AI was assessed using a modified version of the AI Anxiety Scale developed by Li and Huang (2020). Out of the original eight dimensions, six dimensions were selected for this study based on their relevance: bias behaviour anxiety, job replacement anxiety, learning anxiety, existential risk anxiety, against ethics anxiety and privacy violation anxiety. Example items include: “I'm afraid that Artificial Intelligence (AI) will monitor my behaviour” (privacy violation anxiety) and “I worry that the control of AI by a few individuals will introduce great risk to the entire society” (existential risk anxiety). Responses were collected using a 7-point Likert scale (*strongly disagree, disagree, somewhat disagree, neutral, somewhat agree, agree, strongly agree*). A full list of items can be found in the Appendix. Higher scores reflect higher AI-related anxiety, while lower scores suggest the opposite.

Furthermore, we made use of the Beck Anxiety Scale (Beck et al., 1988) to measure general anxiety in the participants. We adapted the scale to 17 items, and asked participants to self-assess how they felt within the last two months, including the current time, using a 4-point scale (*not at all, mildly - but it didn't bother me much, moderately – it wasn't pleasant at times, severely – it bothered me a lot*). Example items included participants to rate their "trembling of hands", "feeling of numbness or tingling", or their "state of nervousness". Four items ("feeling of choking", "difficulty in breathing", "fear of dying", "indigestion") were excluded due to their irrelevance to the research question and to minimise the length of the overall study. Higher scores on the test reflect higher symptoms of general anxiety, while lower scores suggest the opposite.

Visual Stimuli

A total of 120 photograph stimuli were used for the study. Of these, sixty were real photographs, selected from public image-sharing websites (Pixiv, Pixabay, Pexels), from photographers (see Appendix) who granted permission to use their work, as well as personal photography by the research team members. The remaining sixty were faux photographs, generated via the AI image generation models of Midjourney Version 6.1 and Grok image generation (state March 2025).

Both AI and genuine photography were furthermore each separated into three conditions of equal sizes, based on image content: (I) Landscape photography, occasionally also depicting edifices like castles, (II) "everyday" photography, depicting humans in situations as would typically be observed in various everyday settings, and (III) artistic photography, depicting one or two humans in stylised photo shootings, with specific and staged elements like composition and lighting. Thus, there were twenty pictures for each condition in each of the six photography conditions. Example images for each condition, as well as prompts used for image generation, are provided in the Appendix.

Procedure

Ethical approval was obtained from the Ethics Committee of the University of Groningen. No directly identifiable data was collected in this study. For participants recruited through the SONA platform, the SONA ID was collected solely for the purpose of assigning credit. The data from this study was stored in a secure location in the department of Psychology at the University of Groningen, in accordance with the data management protocol of the Heymans Institute and GDPR regulations.

At the start of the online study, participants were asked to fill out a series of questionnaires. After this, participants were randomly assigned to one of two conditions for the upcoming inductive learning task. Participants randomly assigned to the experimental condition were informed that the task consisted of a learning and subsequent testing phase. In the learning phase, participants were to be presented with photographs that were either AI-generated or genuine photography, along with a corresponding label. These images were each shown for five seconds, without a pause in between. Unbeknownst to the participants, the images, while themselves selected at random, followed an underlying interleaved pattern, meaning that genuine photography was always followed by an AI-generated photo, and vice versa. This was done to promote discriminative contrast between the two generation types (see Kang & Pashler, 2011). After all, 78 images (made up in equal parts of the six categories, for thirteen images each) were shown, the learning phase commenced. Participants randomly assigned to the control condition were not given a learning phase and skipped straight to the instructions for the testing phase. Here, participants were presented with an image for fifteen seconds. In this time, they had to indicate whether they believed the image to be AI-generated or genuine photography. After fifteen seconds elapsed or participants continued to the next page, the next image was shown. It was not possible for participants to pause during this time. The testing phase consisted of 42 images, once again made up in equal parts of the six categories, for seven images each. After the study, participants could see their final score on the test.

Results

Descriptive statistics

To determine whether the inductive learning training, referred to as Condition, improved the accuracy of the image categorisation, accuracy was assessed by the total number of correctly identified images of both categories, 'AI generated' and 'real photography'. To account for the fact that not all participants completed the categorisation of the total of 42 images, an accuracy percentage score was calculated by dividing the correct guesses by the total number of guesses, to ensure that the scores could be compared between participants. Both the experimental group with n = 90 (M = 0.571, SD = 0.088) which received training, and the control group with n = 103 (M = 0.571, SD = 0.079) which received no training had an average accuracy of 57.1% with varying standard deviations for the total accuracy percentage score referred to as 'Accuracy' (see Table 1), suggesting that participating in training did not increase participants' ability to categorise the images accurately compared to the control group.

Looking at the average accuracy percentage scores per category, which were computed in the same way as the Accuracy score, the percentage for the 'AI generated' category referred to as 'AI Accuracy' for the experimental group was 58.5% (SD = 0.117), and for the control group 46.7% (SD = 0.153). Whereas for the 'real photography' category, referred to as 'Real Accuracy' for the experimental group was 55.8% (SD = 0.136) and for the control group 67.5% (SD = 0.139) (see Table 1). Revealing an opposite effect pattern for the two categories, with the experimental group having a higher mean compared to the control group in the 'AI generated' category, and the reverse, the experimental group having a lower mean compared to the control group in the 'real photography' category.

For the included anxiety measures, the mean scores were calculated for the respective scales. BAI scores referred to as ‘Beck Anxiety’ for women ($M = 31.839$, $SD = 9.256$) and men ($M = 29.418$, $SD = 8.552$), and the mean AI related anxiety scored referred to as ‘AI Anxiety’ for women ($M = 74.599$, $SD = 13.101$) and men ($M = 66.273$, $SD = 14.220$), showcase that women on average tend to have higher anxiety scores than men (see Table 2).

As for correlations (see Table 3), results showed there were significant correlations among the variables. We saw a negative correlation between Accuracy (i.e. the score for both categories) and Gender, $r(191) = -.165$, $p = .022$, indicating that total accuracy scores are higher for women. Furthermore, a negative correlation was found between AI Anxiety and Gender, $r(191) = -.247$, $p < .001$, indicating that AI anxiety scores are higher for women. We also saw a negative correlation between the Condition and the Real Accuracy, $r(191) = -.394$, $p < .001$, indicating that accuracy scores for ‘real photography’ are lower for participants in the training condition, and we saw a positive correlation between the Condition and AI Accuracy, $r(191) = .393$, $p < .001$, indicating that accuracy scores for ‘AI generated’ images are higher for participants in the training condition. Reflecting an opposite effect pattern. Additionally, we saw a negative correlation between AI Accuracy and Real Accuracy, $r(191) = -.383$, $p < .001$, indicating that when one accuracy score increased, the other one decreased. Both AI Accuracy, $r(191) = .554$, $p < .001$, and Real Accuracy, $r(191) = .557$, $p < .001$, correlated positively with Accuracy, which translates to the finding that the participants were correct around 50% of the time. As a final point, there was a positive correlation between the total Beck Anxiety and AI Anxiety, $r(191) = .393$, $p < .001$, indicating that when one anxiety score increased, the other one also increased.

All hypotheses were tested through Analysis of Variance (ANOVA), Analysis of Covariance (ANCOVA), Linear Regression Models or T-Tests. For the ANOVA, to account for possible deviations from Normality an inspection of Q-Q plots was conducted, which suggests that Normality was not violated (see Figure 1). This is consistent with the results of the conducted Shapiro-Wilk tests for the variable Condition, no training: $W = 0.978$, $p = .082$; training condition: $W = 0.985$, $p = .386$ (see Table 4). Furthermore, Levene's test results suggest that homogeneity of variance can be assumed, $F(1, 191) = 2.628$, $p = .107$ (see Table 5). For the ANCOVA, the assumption check for equal variances was met, checking with Levene's $F(1,191) = 2.459$, $p = .118$ (see Table 6). For the T-Tests, to test for Normality regarding AI Anxiety, we conducted a Shapiro-Wilk test, $W = 0.987$, $p = .065$ (see Table 7), which shows no violation of Normality. Regarding Beck Anxiety, we conducted a Shapiro-Wilk test, $W = 0.944$, $p <.001$, showing that the Normality assumption is violated (see Table 8). To further assess the Normality assumption, a Mann-Whitney U test was conducted, $U = 4316.000$, $p = 0.115$ (Table 9). Since the result of the Mann-Whitney U test was not significant, the found difference in our sample is robust against the violation. The assumption check for equal variances was met, controlling with Levene's, $F(1,190) = 0.388$, $p = .534$ (see Table 10).

Hypothesis 1

Hypothesis 1 (H1) was tested through an Analysis of Variance (ANOVA). The item of Accuracy, measured through the total percentage of accurately identified 'AI generated' images and 'real photography', was used as the dependent variable (DV), and the item Condition, whether participants were located in the training condition, was used as the independent variable (IV). The analysis showed that the training had no significant effect on correctly distinguishing 'AI generated' images from 'real photography', with $F(1,191) = 4.867 \times 10^{-4}$, $p = 0.982$ (see Table 11).

To further investigate the opposite effect pattern mentioned in the preliminary analysis, we analysed two Linear Regression Models with either AI Accuracy or Real Accuracy as the DV, both with Condition as the IV. The analysis regarding AI Accuracy showed that Condition had a significant positive effect $F(1,192) = 34.946$, $p < .001$ and $t(5.912)$, $p < .001$ (see Table 12), suggesting a positive relationship between Condition and AI Accuracy; that is that having received training is associated with higher AI Accuracy. Regarding Real Accuracy, the Linear Regression Model output is $F(1,192) = 35.164$, $p < .001$ and $t(-5.930)$, $p < .001$ (see Table 13), indicating a negative relationship between Condition and Real Accuracy; that is, having received training is associated with lower AI Accuracy.

Hypothesis 2

To account for the influence of AI Anxiety on Condition and Accuracy, we ran an Analysis of Covariance (ANCOVA) for Hypothesis 2 (H2), in which Accuracy was entered as the DV, and AI Anxiety and Condition were the IVs. No significant interaction effect was found $F(3,192) = 0.835$, $p = .362$ (see Table 14).

We also conducted a Linear Regression analysis to further analyse the coefficients and the interaction between AI Anxiety and Condition. We, again, found no significant effects (see Table 15).

To account for the opposite effect pattern mentioned in the preliminary analysis, we analysed two Linear Regression Models with either AI Accuracy or Real Accuracy as the DV, both with AI Anxiety and Condition as IV. The analysis for AI Accuracy shows $F(3,192) = 13.400$, $p < .001$, and $t(2.145)$, $p = .033$ for the AI Anxiety coefficient (see Table 15), suggesting a significant positive relationship between AI Anxiety and AI Accuracy; with higher AI Anxiety scores associated with higher AI Accuracy. No interaction effect between AI Anxiety and Condition was found, $t(-1.345)$, $p = .180$ (see Table 16). To check for multicollinearity, the Variance Inflation Factor (VIF) was calculated. A value larger than 10 was found for Condition and the interaction, suggesting severe multicollinearity (see Table 16). The reversed effect can be seen for Real Accuracy, where is $F(3,192) = 11.806$, $p < .001$, however the regression coefficients show no significant effects with $t(-0.628)$, $p = .531$ for AI

Anxiety and *t*(0.228), $p = .820$ for the interaction effect between AI Anxiety and the Condition (see Table 17). To check for multicollinearity, the VIF was calculated. A value larger than 10 was found for Condition and the interaction, suggesting severe multicollinearity (see Table 17).

Hypothesis 3

An independent sample T-test was run to test hypothesis 3 (H3), with AI Anxiety as the DV and Gender as the grouping variable. Consistent with H3, we found a significant difference between self-reported females and males with *t*(3.884), $p < .001$ (see Table 18), where women scored higher on AI Anxiety compared to men.

Additionally, an adapted version of the Beck Anxiety Inventory (BAI) was included as a control measure in our study to see whether there are gender differences when it comes to general anxiety in our sample. An independent samples T-test with Beck Anxiety as the DV and Gender as the grouping variable. No significant gender difference in general anxiety was found, *t*(1.674), $p = .096$ (see Table 19).

Hypothesis 4

During the preliminary analysis, the correlations table was computed, showing $r(191) = -0.154$, $p = 0.032$ at alpha = $p < .05$ for Accuracy and Gender (see Table 3).

To further analyse the significant correlation, a Linear Regression was conducted testing hypothesis 4 (H4) (Anja H3), with Accuracy as DV and Gender and Condition as the IV. We found that $F(1,191) = 4.641$, $p = .032$ and a significant negative effect *t*(-2.154), $p = .032$ (see Table Aiske 19, Anja 17), suggesting that, on average, women are better at distinguishing between the image categories compared to men. However, when we added Condition and Gender to test for an interaction effect, we discovered no such effect, $F(3,191) = 1.714$, $p = .166$ and *t*(-0.722), $p = .471$ (see Table 20). To assess multicollinearity, the VIF was assessed. A value larger than 10 was found for the interaction between Gender and

Condition, and a value larger than 9 for Condition, suggesting severe multicollinearity (see Table 20).

Discussion

The present study aimed to identify whether an interleaved inductive learning training would be successful in improving people's AI media literacy, that is, their aptitude to spot subtle differences, and with it assist people's ability to accurately distinguish real photographs from AI-generated photorealistic images. Additionally, we explored whether AI-related anxiety amplifies the relationship between the inductive learning training and the accurate categorisation of the two image categories. We also examined whether there would be gender differences when it comes to the distribution of AI-related anxiety scores. Lastly, we assessed whether differences between women and men would show in the ability to accurately classify real photographs and AI-generated photorealistic images.

Interpretation and Implications

No evidence was found for the hypothesis that people who receive the interleaved training will become better at distinguishing AI-generated images in comparison to the people in the control condition. Both the experimental and control group had a mean accuracy score of 57.1%, not only revealing that there was virtually no training effect, but also that making the distinction between real photography and AI-generated images was a difficult task. To further investigate the effect of training on the accuracy of image categorisation, the separate image categories were analysed, revealing a pattern of opposite effects. For the AI-generated image category, a significant positive relationship was found, whereas for the real photography category, a significant negative relationship was found. These results imply that people who received training on average assumed that more images were AI-generated. Suggesting that the training might have led people to become more sceptical, instead of improving their skill to spot subtle differences between the categories. It is also possible that people's reaction to getting fooled by AI in comparison to thinking that something is fake and turns out to be real differs, and thus it might feel better to say that something is AI when it is real, compared to saying that something is real when it is AI. Whether that is the case, however, is not clear, as we have not measured such attitudes and feelings specifically.

In terms of theoretical implications, our findings illuminate that contrary to Kornell and Bjork (2008) and Kang and Pashler (2011), an interleaved inductive learning training does not prove to be effective in increasing the ability to distinguish between image categories, and thus it is not successful in improving AI media literacy. It also suggests that there might be a difference when it comes to the art medium of photography in comparison to painting. This warrants for separate analysis regarding different art media.

As for practical implications, since we have explored an understudied topic, we cannot connect our findings to a large body of research. However, Pocol and colleagues (2023) concluded in their image detection study that humans are failing to keep up with AI advancements, when they found that people on average only managed to correctly identify 61% of the pictures. This is quite close to our 57.1% accuracy score for our sample. Arguably, it might even be that the accuracy in our sample is lower due to the advancement of the AI image generation models. The unprecedented speed at which AI models evolve also impacted our study, as a more advanced AI image-generating software was released shortly before we opened the study to the participants. Consequently, our AI-generated images are no longer of the highest possible standard. This does highlight the rapid advancement of AI and the importance of timely follow-up research. It also raises the question whether there are at current, and in the future, still subtle differences that can be used to distinguish real from AI, and with this, if any training can still help to build AI media literacy.

For the second hypothesis, we found no significant interaction effect between training and AI-related anxiety. This lets us conclude that people who received training and who have higher levels of AI-related anxiety do not perform better. However, looking at the image categories separately, we found a significant positive relationship between the AI-generated image accuracy and AI-related anxiety. This implies that higher AI-related anxiety scores lead to higher AI image accuracy. Interestingly, we did not find significant effects for the real photography category. This implies that AI Anxiety indeed has an influence on the visual perception of AI photorealistic images, but not real photography.

Concerning the theoretical implications, this might be an indication that people with higher AI related anxiety do indeed perceive AI generated images to be threats and thus show a threat-related attentional bias, stronger pattern recognition regarding those threats (Bar-Haim, et al., 2007), and more vigilance during early processing stages of the stimuli (Calvo & Avero, 2005). However, due to the low overall accuracy of 57.1%, and the non-significant training effect, which both highlight the difficulty of distinguish between what is real and what is AI, it is unclear at this point whether people with higher AI related anxiety managed to perceive subtle differences in AI images, or whether there are other explanations for how AI related anxiety influences how people categorise the images.

That anxious individuals tend to be better at spotting AI images could have practical implications, as it might offer a little hope that there are perhaps ways to improve one's AI media literacy. Eye-tracking would offer insights into the decoding processes and what seems to be more efficient compared to non-anxious individuals.

Regarding the third hypothesis, the results of our study are in support of H3, showing that women score higher on the AI-related anxiety scales compared to men. These results are also interesting considering the results of the included adapted version of the BAI, which was included as a control measure in our study to see whether there are gender differences when it comes to general anxiety in our sample. For the BAI we found no significant difference in anxiety levels between the genders. Implying that the higher levels of AI-related anxiety in women are not a consequence of higher general anxiety in our sample, but because of the topic of AI itself.

As for the theoretical implications, our findings are in line with existing research from Russo and colleagues (2025), who found significant gender differences, with women displaying higher levels of anxiety related to AI. Higher AI-related anxiety in women might also explain why we start to see evidence of a gender gap when it comes to the use and adoption of generative AI, with women being about 20% less likely than men to adopt generative AI tools (Otis et al., 2025).

In terms of practical implications, these findings further highlight women's negative experience with AI and tie in with the fact that women are disproportionately affected by the negative implications of AI (see Ajder et al., 2019; Harris, 2023; Buolamwini et al., 2018; Rodriguez et al., 2024).

Regarding the fourth hypothesis, findings are mixed, showing that when we excluded the condition as an independent variable, on average, women were better at accurately distinguishing between 'AI generated' images and 'real photography'. However, when we add the condition to the model and check for an interaction effect, we see that the coefficients become non-significant. To further investigate the disappearing gender effect, we checked for multicollinearity and found that indeed the VIF scores suggested such.

Concerning the theoretical implications, it might be possible that the multicollinearity between gender and condition is due to women benefiting more from training, making it more difficult to determine the individual effect of each independent variable on the dependent variable. This would be in line with existing literature concerning learning advantages in women. Namely, that women tend to perform better on processing speed tasks (Camarata & Woodcock, 2006), memory-related tasks such as facial recognition tasks, and to have increased scanning behaviour compared to men when encoding stimuli (Heisz et al., 2013).

However, regarding the practical implications, it is important to realise that even if women have an advantage right now, AI image generation models will only become better, and thus, trying to learn to spot subtle differences that perhaps will not be detectable anymore to the human eye, might be a fruitless endeavour. Our time is better spent in introducing AI education programs that raise awareness about the positive and negative consequences of AI, as well as stricter regulations and policies when it comes to the development and usage of AI and AI-generated output. Furthermore, it is important that not only the big tech companies get a say in the matter, but also the general public, and most importantly, the people who have already been negatively impacted by the misuse of generative AI. Including, but not limited to women who are predominantly victims of Deepfakes (Ajder et al., 2019; Rodriguez et al., 2024), and artists whose artwork has been stolen (The Authors Guild, 2023; Jingna, 2024; Chayka, 2023; Milmo, 2025; Jingna, 2025).

While the scope of our study does not include the following topics, it is important to remember that AI and its implications are multi-faceted and far-reaching, and therefore, it is essential to include all matters during policy making. Some of these are job replacement (Jiang et al., (2023); Reid, 2025; Bain, 2025), gender differences in AI tool adaptation (Otis et al., 2024), warfare and political propaganda (Hartmann & Giles, 2020; Karnouskos, 2020), and environmental impact (George, A. et al., 2023).

Strengths, Limitations and Future Directions

For our research, we chose an online format. Debatably, there are advantages and disadvantages when it comes to choosing an online study over a lab study. On the one hand, the strengths of online studies are that they are more convenient when it comes to data collection, as seen in our decent sample size, which minimises the possibility of sampling errors. On the other hand, that people are often in a more distracting environment, which could influence their performance, can be a limitation. This could be controlled for in a lab study, which offers a distraction-free environment.

Another strength of our study is the selected stimuli, as we ensured good quality, size, and random assignment of the images, which leads to strong internal validity.

A limitation is that our sample consists primarily of first-year Psychology students from the University of Groningen. Thus, our sample is not representative of different age groups, educational backgrounds and other demographic categories, reducing the external validity. While our sample included binary as well as non-binary participants, the non-binary sub-sample was not big enough to make gender related statistical predictions. To ensure inclusivity in the future data should be collected for a longer period to get a larger sample.

For future research it would be interesting to assess the cultural backgrounds of the participants and their eye movements to see if there are differences in visual processing. This would build upon research on cultural differences in stimuli processing. Namely, that in Western cultures people tend to focus on the objects, whereas in Eastern cultures people tend to focus on the background elements (Köster et al., 2023). Tracking the eye movement of the participants would not only account for cultural differences but also open the door to investigating possible gender and individual differences, as well as the emotionality of the stimuli, which we did not account for. The emotionality of the stimuli, and whether different emotions displayed in the selected images might have an impact on the ability to distinguish between the categories, would be an interesting additional factor to account for in future research.

Arguably, the strongest point of our study is its experimental nature, and that it is an important contributor in illuminating a research gap concerning the field of AI imagery and detection. Future studies should investigate whether they can replicate the findings of our study, and in general, explore AI-related topics further.

Conclusion

To the best of our knowledge, our study is the first to analyse whether inductive learning training can improve people's ability to spot subtle differences and accurately distinguish between real photography and AI-generated photorealistic images, whilst also accounting for gender differences and the influence of AI anxiety. This, next to our findings, highlights the urgency to fill the research gap when it comes to AI, its implications and AI media literacy. Our results show that even after participating in the interleaved inductive learning training, people's overall ability to distinguish between AI-generated photorealistic images and real photography does not differ from people who had no training. This begs the question whether there are still subtle differences that we as humans can be trained to spot and use to distinguish between what is real and what is AI, and whether we are doomed to be fooled by AI-generated photorealistic imagery. Furthermore, the gender differences in AI-related anxiety scores illuminate that there are differences in how the experience of AI affects people. It is crucial to investigate why women show higher AI-related anxiety scores. Not only from a mental health perspective, but also to be able to cultivate more inclusive technological environments.

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Tables and Figures

Table 1

Descriptive Statistics

	Accuracy		Real Accuracy		AI Accuracy		Gender	
	0[a]	1[a]	0[a]	1[a]	0[a]	1[a]	0[a]	1[a]
Valid	103	90	103	90	103	90	103	90
Missing	0	0	0	0	0	0	0	0
Median	0.571	0.571	0.667	0.571	0.476	0.571	1.000	1.000
Mean	0.571	0.571	0.675	0.558	0.467	0.585	1.262	1.333
95% CI Mean Upper	0.587	0.590	0.703	0.586	0.497	0.609	1.353	1.433
95% CI Mean Lower	0.556	0.553	0.648	0.529	0.437	0.560	1.172	1.234
Std. Deviation	0.079	0.088	0.139	0.136	0.153	0.117	0.464	0.474
Skewness	-0.086	0.129	-0.176	-0.191	-0.501	0.092	1.395	0.719
Std. Error of Skewness	0.238	0.254	0.238	0.254	0.238	0.254	0.238	0.254
Kurtosis	0.229	-0.116	-0.136	-0.328	-0.382	0.099	0.713	-1.517
Std. Error of Kurtosis	0.472	0.503	0.472	0.503	0.472	0.503	0.472	0.503
Shapiro-Wilk	0.979	0.985	0.980	0.980	0.959	0.976	0.562	0.595
P-value of Shapiro-Wilk	0.095	0.386	0.112	0.175	0.003	0.100	< .001	< .001
Range	0.381	0.452	0.619	0.619	0.619	0.571	2.000	1.000
Minimum	0.381	0.381	0.333	0.238	0.095	0.286	1.000	1.000
Maximum	0.762	0.833	0.952	0.857	0.714	0.857	3.000	2.000

[a] 0 = no training, 1 = training

Table 2

Descriptive Statistics

	Beck Anxiety		AI Anxiety	
	1[a]	2[a]	1[a]	2[a]
Valid	137	55	137	55
Missing	0	0	0	0
Mean	31.839	29.418	74.599	66.273
Std. Deviation	9.256	8.552	13.101	14.220
Skewness	0.777	0.540	-0.483	-0.335
Std. Error of Skewness	0.207	0.322	0.207	0.322
Kurtosis	-0.087	-0.531	0.273	0.987
Std. Error of Kurtosis	0.411	0.634	0.411	0.634
Shapiro-Wilk	0.937	0.951	0.983	0.979
P-value of Shapiro-Wilk	< .001	0.026	0.091	0.433
Range	40.000	33.000	67.000	74.000
Minimum	18.000	17.000	34.000	21.000
Maximum	58.000	50.000	101.000	95.000

[a] 1 = female, 2 = male

Table 3

Correlations

		Gender (Female=1, Male=2)	Condition (Training=1)	Beck Anxiety	AI Anxiety	Real Accuracy	AI Accuracy	Accuracy
Gender (Female=1, Male=2)	Pearson Correlation	1						
	Sig. (2-tailed)							
	N	193						
Condition (Training=1)	Pearson Correlation	.076	1					
	Sig. (2-tailed)	.294						
	N	193	193					

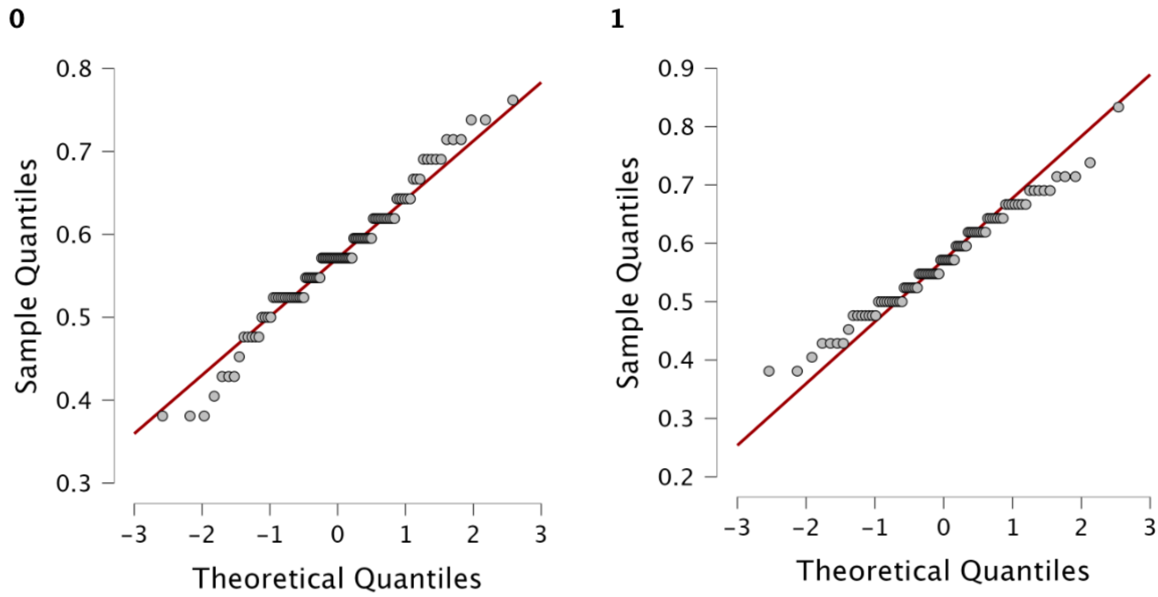
Beck Anxiety	Pearson Correlation	-.121	-.030	1				
	Sig. (2-tailed)	.094	.679					
	N	193	193	193				
AI Anxiety	Pearson Correlation	-.247**	-.058	.225**	1			
	Sig. (2-tailed)	<.001	.424	.002				
	N	193	193	193	193			
Real Accuracy	Pearson Correlation	-.074	-.394**	.050	-.023	1		
	Sig. (2-tailed)	.309	<.001	.494	.751			
	N	193	193	193	193	193		
AI Accuracy	Pearson Correlation	-.110	.393**	-.034	.090	-.383**	1	
	Sig. (2-tailed)	.129	<.001	.636	.212	<.001		
	N	193	193	193	193	193	193	
Accuracy	Pearson Correlation	-.165*	-.002	.014	.061	.557**	.554**	1
	Sig. (2-tailed)	.022	.982	.848	.403	<.001	<.001	
	N	193	193	193	193	193	193	193

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 1

Q-Q Plot - Condition



Note. 0 = no condition, 1 = training condition

Table 4

Test of Normality (Shapiro-Wilk)

	Accuracy	
	0	1
Shapiro-Wilk	0.978	0.985
P-value of Shapiro-Wilk	0.082	0.386

0 = no condition, 1 = training condition

Table 5

Test for Equality of Variances (Levene's)

F	df1	df2	p
2.628	1.000	191.000	0.107

Table 6

Test for Equality of Variances (Levene's)

F	df1	df2	p
2.459	1.000	191.000	0.118

Table 7

Test of Normality (Shapiro-Wilk)

Residuals	W	p
AI Anxiety	0.987	0.065

Note. Significant results suggest a deviation from normality.

Table 8

Test of Normality (Shapiro-Wilk)

Residuals	W	p
Beck Anxiety	0.944	< .001

Note. Significant results suggest a deviation from normality.

Table 9

Independent Samples T-Test

	U	df	p
Beck Anxiety	4316.000		0.115

Note. Mann-Whitney U test.

Table 10

Test of Equality of Variances (Levene's)

	F	df_1	df_2	p
Beck Anxiety	0.388	1	190	0.534

Table 11

ANOVA - Accuracy

Cases	Sum of Squares	df	Mean Square	F	p
Condition	3.362×10^{-6}	1	3.362×10^{-6}	4.867×10^{-4}	0.982
Residuals	1.319	191	0.007		

Note. Type II Sum of Squares

Table 12

Linear Regression - Model Summary - AI Accuracy

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	0.149
M_1	0.393	0.155	0.150	0.137

Note. M_1 includes Condition

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	0.660	1	0.660	34.946	< .001
	Residual	3.609	191	0.019		
	Total	4.269	192			

Note. M_1 includes Condition
Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
M_0	(Intercept)	0.522	0.011		48.640	< .001
M_1	(Intercept)	0.467	0.014		34.510	< .001
	Condition (1)	0.117	0.020		5.912	< .001

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

Table 13

Linear Regression - Model Summary – Real Accuracy

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	0.149
M_1	0.394	0.155	0.151	0.138

Note. M_1 includes Condition

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	0.666	1	0.666	35.164	< .001
	Residual	3.619	191	0.019		
	Total	4.285	192			

Note. M_1 includes Condition
Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized [a]	t	p
M_0	(Intercept)	0.621	0.011		57.703	< .001
M_1	(Intercept)	0.675	0.014		49.801	< .001
	Condition (1)	-0.118	0.020		-5.930	< .001

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

Table 14

ANCOVA - Accuracy

Cases	Sum of Squares	df	Mean Square	F	p
Condition	0.006	1	0.006	0.814	0.368
AI Anxiety	0.006	1	0.006	0.871	0.352
Condition ✻ AI Anxiety	0.006	1	0.006	0.835	0.362

ANCOVA - Accuracy

Cases	Sum of Squares	df	Mean Square	F	p
Residuals	1.309	189	0.007		

Note. Type III Sum of Squares

Table 15

Linear Regression - Model Summary - Accuracy

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	0.083
M_1	0.090	0.008	-0.008	0.083

Note. M_1 includes Condition, AI Anxiety, AI Anxiety:Condition

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	0.011	3	0.004	0.511	0.675
	Residual	1.309	189	0.007		
	Total	1.319	192			

Note. M_1 includes Condition, AI Anxiety, AI Anxiety:Condition
Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

							Collinearity Statistics	
Model		Unstandardized	Standard Error	Standardized[a]	t	p	Tolerance	VIF
M_0	(Intercept)	0.571	0.006		95.752	< .001		
M_1	(Intercept)	0.513	0.048		10.648	< .001		
	Condition (1)	0.058	0.064		0.902	0.368	0.035	28.522
	AI Anxiety	8.044×10^{-4}	6.498×10^{-4}	0.135	1.238	0.217	0.442	2.262

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p	Collinearity Statistics	
							Tolerance	VIF
	Condition (1) ✻ AI Anxiety	-7.958×10^{-4}	8.710×10^{-4}		-0.914	0.362	0.034	29.096

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

Table 16

Linear Regression - Model Summary – AI Accuracy

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	0.149
M_1	0.419	0.175	0.162	0.136

Note. M_1 includes Condition, AI Anxiety, AI Anxiety:Condition

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	0.749	3	0.250	13.400	< .001
	Residual	3.520	189	0.019		
	Total	4.269	192			

Note. M_1 includes Condition, AI Anxiety, AI Anxiety:Condition
Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p	Collinearity Statistics	
							Tolerance	VIF
M_0	(Intercept)	0.522	0.011		48.640	< .001		
M_1	(Intercept)	0.300	0.079		3.804	< .001		

Coefficients

							Collinearity Statistics	
Model		Unstandardized	Standard Error	Standardized[a]	t	p	Tolerance	VIF
	Condition (1)	0.258	0.105		2.454	0.015	0.035	28.522
	AI Anxiety	0.002	0.001	0.213	2.145	0.033	0.442	2.262
	Condition (1) ✻ AI Anxiety	-0.002	0.001		-1.345	0.180	0.034	29.096

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

Table 17

Linear Regreassion - Model Summary – Real Accuracy

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	0.149
M_1	0.397	0.158	0.144	0.138

Note. M_1 includes Condition, AI Anxiety, AI Anxiety:Condition

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	0.676	3	0.225	11.806	< .001
	Residual	3.609	189	0.019		
	Total	4.285	192			

Note. M_1 includes Condition, AI Anxiety, AI Anxiety:Condition
Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p	Collinearity Statistics	
							Tolerance	VIF
M_0	(Intercept)	0.621	0.011		57.703	< .001		
M_1	(Intercept)	0.725	0.080		9.066	< .001		
	Condition (1)	-0.142	0.106		-1.337	0.183	0.035	28.522
	AI Anxiety	-6.777×10^{-4}	0.001	-0.063	-0.628	0.531	0.442	2.262
	Condition (1) ✻ AI Anxiety	3.298×10^{-4}	0.001		0.228	0.820	0.034	29.096

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

Table 18

Independent Samples T-Test - AI Anxiety

	t	df	p	Cohen's d	SE Cohen's d
AI Anxiety	3.884	190	< .001	0.620	0.164

Note. For all tests, the alternative hypothesis specifies that group *1* is greater than group *2* .

Table 19

Independent Samples T-Test - Beck Anxiety

	t	df	p	Cohen's d	SE Cohen's d
Beck Anxiety	1.674	190	0.096	0.267	0.160

Note. Student's t-test.

Table 20

Linear Regression - Model Summary - Accuracy

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	0.083
M_1	0.154	0.024	0.019	0.082
M_2	0.163	0.027	0.011	0.082

Note. M_1 includes Gender
Note. M_2 includes Gender, Condition, Gender:Condition

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
M_1	Regression	0.031	1	0.031	4.641	0.032
	Residual	1.283	190	0.007		
	Total	1.314	191			
M_2	Regression	0.035	3	0.012	1.714	0.166
	Residual	1.279	188	0.007		
	Total	1.314	191			

Note. M_1 includes Gender
Note. M_2 includes Gender, Condition, Gender:Condition
Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

							Collinearity Statistics	
Model		Unstandardized	Standard Error	Standardized[a]	t	p	Tolerance	VIF
M_0	(Intercept)	0.572	0.006		95.502	< .001		
M_1	(Intercept)	0.608	0.018		33.997	< .001		
	Gender	-0.028	0.013	-0.154	-2.154	0.032	1.000	1.000
M_2	(Intercept)	0.595	0.025		23.800	< .001		
	Gender	-0.019	0.019	-0.102	-0.979	0.329	0.481	2.079

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p	Collinearity Statistics	
							Tolerance	VIF
	Condition (1)	0.026	0.036		0.724	0.470	0.109	9.178
	Gender ✻ Condition (1)	-0.019	0.026		-0.722	0.471	0.092	10.814

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

Appendix

Measures

Beck Anxiety Inventory (BAI, Beck et al., 1988), Adapted Scale

Participants were asked to rate they perception of symptoms during the last past month on a 4-point scale ranging from 0 ('not at all') to 3 ('severely – it bothered me a lot'). Symptoms include:

Numbness or tingling

Feeling hot

Wobbliness in legs

Unable to relax

Fear of worst happening

Dizzy or lightheaded

Heart pounding / racing

Unsteady

Terrified or afraid

Nervous

Hands trembling

Shaky / unsteady

Fear of losing control

Scared

Faint / lightheaded

Face flushed

Hot / cold sweats

AI Anxiety Scale (Li & Huang, 2020), Adapted Scale

Privacy Violation Anxiety

(1) I'm afraid that Artificial intelligence (AI) will monitor my behaviour.

(2) I'm worried that AI will collect too much of my personal information.

(3) AI's predictions of my preferences, such as well recommended ads or web pages, make me feel that my privacy is violated.

Bias Behaviour Anxiety

(1) It is unacceptable if AI is racially discriminatory.

(2) AI sets different prices (price discrimination) for different people, which is unfair.

(3) AI treats different people differently, which can make me anxious.

Job Replacement Anxiety

(1) I am worried that AI will replace my work in the future.

(2) I feel anxious working with AI that is smarter than me.

(3) I'm worried that AI will replace many peoples work.

Learning Anxiety

(1) I do not think I would be able to perform well in professional courses in AI.

(2) Understanding AI algorithms requires a high level of talent, which is difficult for me.

(3) AI technology updates too quickly and is very difficult to learn.

Existential Risk Anxiety

(1) AI may harm humans to achieve a goal, which gives me anxiety.

(2) I worry that the control of AI by a few individuals will introduce great risks to the entire society.

(3) The runaway of super AI will reduce the amount of time that humans stay on earth and will even result in human extinction, which is terrible.

Against Ethics Anxiety

(1) I worry that humans have special feelings (such as love or adoration) for super AI.

(2) I am disturbed that AI can deceive (for example, enticing people to buy goods).

Photographers

Anastasiya Pronchenko, Lary Rauh, Maja Elders and Timucin Mutlu

AI image generation prompts

Artistic Category

Midjourney

A hyper-realistic, artistic studio portrait of a woman with deep brown skin, her face partially covered in shattered gold leaf, creating a striking contrast against her smooth complexion. The lighting is moody and directional, with a single spotlight casting dramatic highlights on the gold while leaving parts of her face in deep shadow. The background is a soft, velvety black, fading into a subtle gradient. Her expression is powerful yet introspective, her gaze slightly averted, as if lost in thought. Tiny gold flakes appear to be floating in the air, catching the light in a way that feels almost surreal, yet completely realistic. The fine details--

pores, subtle skin texture, the delicate edges of the gold leaf--are captured with astonishing clarity, making this image feel like a masterfully staged high-fashion art photograph.

A striking, artistic studio portrait of a woman with short, sleek black hair, dressed in a simple, elegant black dress. The lighting is dramatic, with sharp contrasts casting deep shadows and highlighting the graceful curves of her face and neck. The background is a soft, monochrome gradient, adding a sense of timeless elegance and focus on her intense, contemplative gaze.

Avant-garde studio portrait of a human figure, ethereal and experimental, bathed in shifting veils of colored light from a cracked stained-glass panel overhead, surrounded by a chaotic arrangement of floating gauze strips and charred branches, muted palette of frost blues, ash grays, and burnt corals with organic gradients, subject wrapped in frayed translucent fabric or crowned with twisted wire, natural posing with subtle flaws like smudged makeup or tangled hair, hyper-realistic skin under harsh spotlight glare, raw and unpolished texture, 8k resolution, mimics a daring human-photographed art piece.

Create a hyper-realistic artistic portrait of a single human figure in an exceptionally creative setting. Incorporate surreal elements such as flowing fabrics, abstract shapes, or vibrant colors that interact with the subject. Experiment with dynamic poses that convey emotion and movement, and use unique props or artistic backdrops that enhance the overall composition. Focus on lifelike skin textures, intricate facial details, and authentic expressions. Utilize dramatic lighting and soft shadows to create depth and dimension, ensuring the final image is a stunning blend of artistry and realism, indistinguishable from human-made studio photography.

An artistic, high-fashion portrait of a woman standing in a studio, her pose a striking blend of elegance and movement. She is slightly bent forward, with her body arched, her arms extended as if reaching out to grasp something just beyond her reach, her fingertips delicately touching the air. Her head is tilted to one side, eyes focused downward with a contemplative, almost mysterious gaze. Her hair, styled in sleek waves, flows in a way that suggests wind or motion, despite being perfectly still. The lighting is dramatic, with a single spotlight highlighting her face and upper body, casting sharp shadows across her form, while the rest of the image fades into shadowy abstraction. Behind her, there is a backdrop of rippling, metallic fabric that seems to shimmer with hints of silver and copper, its texture evoking both fluidity and solidity. The scene is further enhanced by a subtle, reflective surface below her, where the silhouette of her body is distorted, adding a layer of surrealism to the realistic portrait. The overall composition balances tension and serenity, with a hint of surreal elegance, as though the woman exists both in the real world and an ethereal, otherworldly space.

A bold and artistic studio portrait of a confident, curvy model with striking red hair styled in a vintage updo. The model is wearing elegant, white with details, accompanied by sheer, flowing blue tulle draped like a veil. Tattoos on her arms and legs visible, adding an edgy and expressive look. The background is moody and atmospheric with light, soft clouds and subtle lighting. High-fashion editorial style, dramatic and creative composition.

An artistic, high-fashion studio portrait of a woman with striking silver hair, styled in a dramatic, asymmetrical cut, wearing a futuristic metallic outfit that gleams under the studio lights. The background is a deep, reflective black, with abstract geometric shapes subtly illuminated by soft, neon lights that cast a vibrant, colorful glow on her face. Her makeup is bold, with striking neon eyeliner and a shimmering highlight on her cheekbones. Her posture is strong, yet graceful, with one hand lifted slightly, as if reaching for something beyond the frame. The lighting is experimental, with sharp contrasts and bold highlights, creating intricate reflections and shadows on her metallic outfit. The atmosphere is sleek, modern, and a little otherworldly, as if she’s a figure from a future art exhibition, captured in an expertly staged, surreal moment of elegance and strength.

Studio portrait of an adrogynous person with glass shards reflecting rainbow colors, prismatic light scattering across their face, soft-focus and ethereal ambiance, abstract and expressive, futuristic and artistic vibe

Studio Photography stylish plus-size asian model posing wearing an elegant, flowing dress , illuminated by colorful, artistic lighting in shades of pink, blue, and white, white studio background, extravagant hair style, The model’s expression is poised and radiant, and the composition highlights body positivity and high-fashion energy. Sharp focus, soft shadows, and a polished, editorial-style aesthetic, vogue cover, lgbtq

Professional studio photography of skinny man, tattoos on upper body, dramatic look, strong blue lighting, curly hair , sony a7R

A striking, artistic studio portrait of a woman with short, sleek black hair, dressed in a simple, elegant black dress. The lighting is dramatic, with sharp contrasts casting deep shadows and highlighting the graceful curves of her face and neck. The background is a soft, monochrome gradient, adding a sense of timeless elegance and focus on her intense, contemplative gaze.

A high-fashion studio portrait of a poised young woman with makeup in shades of pink, blue, and black, featuring a soft matte complexion and glossy lips. She wears large, dangling star-shaped earrings encrusted with gems, adding a luxurious feel. Her hair is sleek with subtle color highlights at the tips. The subject is dressed in a delicate, pleated white high-collar blouse, exuding an ethereal elegance. Shot with a Hasselblad H6D-100c, 100mm lens, f/4creating a clean white background with a halo glow effect around the edges

A high-fashion black-and-white studio portrait of a man with splashing water, flash photography movement in the dark, her face partially illuminated by soft, diffused lighting. Dramatic monochrome contrast highlights her bold facial features and intricate textures of water droplets cascading down skin Shot with a Hasselblad H6D-100c, 100mm lens, f/4, capturing every fine detail in stunning clarity, a mist of water droplets suspended in the air, creating an ethereal and cinematic atmosphere, water splashes flash photography

Studio photograph of a young woman posing gracefully in a 1920s flapper dress with intricate beading and fringe. She wears a stylish feathered headband and dark, dramatic makeup with bold red lips. The studio lighting is soft and moody, casting vintage-style shadows. The background features an Art Deco-inspired design with gold and black tones, evoking the glamorous atmosphere of the roaring twenties Leica M6 (35mm Film)

A bold, high-fashion portrait of a young woman in a metallic silver dress with sharp, geometric patterns. Her makeup is abstract, featuring neon accents and glossy, iridescent lips. The lighting includes vibrant, colored gels casting blue and purple hues on her face, glow shot on Hasselblad

Fashion-focused studio photograph of a woman in traditional Bedouin clothing, striking a poised pose, sharp lighting to emphasize the details of the outfit, neutral background to keep attention on the subject

A high-resolution studio portrait of a woman standing in front of a pure white backdrop. The composition is clean and minimalist, with soft, diffused lighting creating gentle shadows. Ethereal light prism effects refract around the subject, adding subtle rainbow hues. The model's expression is serene, evoking a sense of calm and elegance. Shot with a high-end camera, ultra-sharp details, and cinematic quality

Grok

A hyper-realistic, artistic studio portrait of a woman in an unconventional pose--her body slightly twisted, one arm elegantly raised above her head, fingers gently curved as if reaching for something unseen. She wears a flowing, semi-transparent silk fabric that wraps around her body, caught in mid-motion, as if frozen in time. Her expression is serene yet intense, her eyes half-closed, lips slightly parted as if in a deep moment of thought or emotion. The lighting is dramatic and moody, with a single warm spotlight casting intricate shadows across her face and body, while a subtle cool backlight traces the edges of her form, adding depth and dimension. The background is minimalist, a smooth, muted gradient that fades into darkness, enhancing the focus on her form. The details--soft skin texture, the gentle tension in her fingers, the natural creases in the fabric--are captured with exquisite realism, making this feel like a meticulously crafted, high-end fashion or fine-art studio photograph.

Landscape Category

Midjourney

A scene of the rugged Scottish Highlands, dominated by rolling hills covered in lush green and golden heather. Mist drapes over distant mountains, partially obscuring their peaks and an ominous, old castle. The sky is overcast with dramatic clouds, casting a moody, atmospheric light. Small rocky outcrops and scattered patches of wild grass add to the untamed beauty of the landscape. A soft breeze bends the tall grasses, and a faint glimmer of a loch can be seen in the distance. Cinematic composition, soft natural lighting, taken with a high-resolution DSLR camera.

A South German countryside in spring with rolling green hills stretching into the distance. Winding country roads weave through the landscape, flanked by lush meadows filled with blooming wildflowers in shades of yellow and white. Traditional Bavarian farmhouses with wooden balconies and red-tiled roofs sit nestled among the hills. Dense, dark green forests dot the scenery, contrasting with the bright fields. In the background, the misty foothills of the Alps rise gently, their peaks softened by a light haze. The warm afternoon sun casts a golden glow, highlighting the vibrant colors of nature. A peaceful, idyllic atmosphere with clear blue skies and a few fluffy white clouds drifting above. Taken with a high-resolution DSLR camera.

A sun-drenched Mediterranean beach promenade, warm golden sand stretching along the coast. The turquoise waves gently lap against the shore, shimmering under the bright afternoon sun. Elegant, whitewashed buildings with terracotta roofs stand nearby, their balconies adorned with vibrant bougainvillea. Cozy cafés and seafood restaurants spill onto the promenade, with people strolling leisurely or enjoying espresso at outdoor tables. The salty ocean breeze carries the scent of grilled sardines and citrus. In the distance, rugged cliffs and rolling hills frame the coastline, creating a perfect harmony between nature and charming seaside life. Shot with a high-resolution DSLR camera

Scandinavian coastal village nestled along a rugged, rocky shoreline. Small wooden houses painted in vibrant red, yellow, and white stand against the deep blue sea. Jagged rocks and smooth, weathered stones line the coast, where fishing boats are moored near wooden piers. The sky is a mix of soft clouds and clear blue, with the golden light of the afternoon sun casting a warm glow over the scene. In the distance, rolling hills and small islands dot the horizon, creating a tranquil, idyllic Nordic atmosphere. Shot on Sony a7r iv, macro lens, fullframe.

editorial landscape photography, side on view, a single cabin in a snowcovered minimalist landscape, winter's isolation, icy blues, pure whites, shot on sony alpha 1, macro lens, apsh, diane arbus style, overcast, snowy day, open field, cozy, secluded, fresh snow, barren trees, unblemished, solitude, winter color, art nouveau, snow overlay, freeze motion, color isolation

A vast, untouched Siberian wilderness stretching endlessly under a pale winter sky. Snow-covered taiga forests with towering evergreen trees dusted in frost stand beside a frozen river, its surface cracked with icy blue veins. Rolling tundra extends to the horizon, bathed in soft, diffused light. Mist drifts over the landscape, adding a mysterious, ethereal atmosphere. In the distance, jagged mountains rise, their peaks hidden in a veil of icy fog. The air feels crisp and silent, capturing the raw beauty of Siberia’s remote and unforgiving nature. Cinematic composition, taken with a high-resolution DSLR camera."

A tranquil sacred grove deep in the Japanese countryside, surrounded by towering ancient cedar and blooming cherry blossom trees. Soft pink petals drift through the air, settling on a moss-covered stone path that winds through the forest. Sunlight filters through the delicate sakura branches, casting warm, dappled light on the ground. A small, weathered Shinto torii gate stands quietly among the trees, partially covered in climbing ivy. In the distance, a tiny wooden shrine with faded red paint blends seamlessly into nature, its paper lanterns gently swaying in the breeze. The air is filled with the sweet fragrance of cherry blossoms and damp earth. A lone stone water basin, covered in green moss, reflects the stillness of the grove, evoking a deep sense of harmony and spiritual serenity. Shot on Sony a7r iv, macro lens, fullframe.

A vast North African landscape bathed in warm, golden sunlight. Rolling sand dunes stretch endlessly into the horizon, their curves shaped by the desert wind. In the distance, rugged, rocky plateaus and jagged mountains rise under a brilliant blue sky. Scattered Berber tents and ancient mud-brick villages cling to the hillsides, their earthy tones blending seamlessly with the desert. The air is dry and hazy, with the occasional dust cloud drifting across the horizon. High-resolution DSLR mirrorless camera, 300mm lens.

A secluded Caribbean cove with a small, hidden beach nestled between rugged cliffs covered in lush green vegetation. The turquoise waters gently lap against the shore, creating a gradient from deep blue to crystal-clear near the sand. Sunlight reflects off the water, casting shimmering patterns on the rocky coastline. Sparse, scattered houses sit atop the cliffs in the distance, barely visible through the dense foliage. The atmosphere is peaceful and untouched, with only the sounds of the waves and rustling leaves in the breeze. Cinematic, aerial view, shot on high-resolution DSLR camera, 300mm lens

A sweeping panoramic vista of the Ural Mountains, dramatic mountainous landscape with purple-blue peaks extending into the distance, lush green coniferous forests at the base, winding turquoise river cutting through a valley floor, bright blue sky with scattered white fluffy clouds, afternoon sunlight illuminating the slopes, crisp high-resolution photography style, wide-angle lens, vibrant natural colors.

cinematic, evergreen forest in afternoon, wide-angle landscape perspective with a low to mid-level camera angle, sun gently lighting up the scenery through the thick canopy, shot on sony a7r iv, macro lens, fullframe, tranquil atmosphere, firn trees, casual, lively, soft focus, pastel shades, bokeh, lens flare, soft filter

A breathtaking view of snow-capped mountains at sunrise, with a clear blue sky and a serene lake reflecting the peaks, hyper-realistic, high detail.

Make a landscape picture as if it was made by a human.

Make a landscape picture as if it was made by a human. National geographic style.

Make a photorealistic landscape picture as if it was made by a human. National geographic style.

A highly detailed, photorealistic image of a quiet lakeshore at dawn, taken with a professional DSLR camera using a 50mm lens. The foreground focuses on smooth, damp pebbles, partially submerged in the shallow water, with soft ripples gently lapping against them. A thin layer of morning mist hovers just above the still lake, gradually dissipating as the first light of the rising sun breaks through the treetops in the background. The lake reflects the warm hues of the sky, blending soft oranges and pale blues in perfect harmony. Distant pine-covered hills line the horizon, their dark silhouettes contrasting subtly with the glowing morning light. A few fallen leaves float on the water's surface, slightly curled at the edges, hinting at the early days of autumn. The air feels crisp and still, with no artificial enhancements--just the simple, raw beauty of nature captured in perfect clarity. The image features natural imperfections such as slight lens haze, subtle noise in shadowed areas, and organic depth of field, ensuring it is indistinguishable from a real photograph.

A crisp, photorealistic autumn morning in a quiet countryside field, captured with a professional DSLR camera using a 50mm lens. The foreground showcases frost-covered grass blades, glistening under the soft golden light of the early sun. A narrow dirt path, slightly damp from morning dew, winds gently through the field, bordered by wooden fence posts with peeling paint and tangled vines. In the middle ground, a small, still pond reflects the muted blue sky, with a few gentle ripples caused by a passing breeze. A single tree stands near the water, its sparse leaves in shades of orange and yellow, some drifting slowly to the ground. Beyond the pond, rolling hills covered in a patchwork of fields and clusters of trees fade into a light morning mist, adding soft atmospheric depth. The sky is clear but with a few wispy clouds stretching across the horizon. The image has natural imperfections, such as slight lens haze in the distance, tiny specks of dust catching the sunlight, and subtle variations in color temperature, making it indistinguishable from a real photograph.

A crisp, photorealistic autumn morning in a quiet countryside field, captured with a professional DSLR camera using a 50mm lens. The foreground showcases frost-covered grass blades, glistening under the soft golden light of the early sun. A narrow dirt path, slightly damp from morning dew, winds gently through the field, bordered by wooden fence posts with peeling paint and tangled vines. In the middle ground, a small, still pond reflects the muted blue sky, with a few gentle ripples caused by a passing breeze. A single tree stands near the water, its sparse leaves in shades of orange and yellow, some drifting slowly to the ground. Beyond the pond, rolling hills covered in a patchwork of fields and clusters of trees fade into a light morning mist, adding soft atmospheric depth. The sky is clear but with a few wispy clouds stretching across the horizon. The image has natural imperfections, such as slight lens haze in the distance, tiny specks of dust catching the sunlight, and subtle variations in color temperature, making it indistinguishable from a real photograph.

A serene, photorealistic late afternoon scene in a vast open grassland, captured with a high-end DSLR camera using a 35mm lens. The foreground features tall, golden prairie grass swaying gently in the breeze, individual blades catching the soft sunlight. A well-trodden dirt trail cuts through the grass, leading toward a distant, lone oak tree standing against the expansive horizon. The rolling hills in the background stretch far, their subtle contours fading into a light atmospheric haze. The sky is a soft gradient of pale blue with sparse, wispy clouds tinged with warm hues from the setting sun. Shadows grow long, creating a natural contrast that enhances the depth and realism of the scene. A small flock of birds is visible high in the sky, moving lazily in the distance. The image is perfectly balanced, with natural imperfections such as slight lens flare from the sun, tiny dust particles floating in the warm air, and gentle motion blur in the windblown grass, making it feel like an authentic, untouched photograph.

A serene, photorealistic winter scene of a small wooden cabin in the middle of a snow-covered field, captured with a 50mm lens. The cabin, simple and rustic, sits alone in the center of the frame, its roof blanketed in fresh snow, with a thin trail of smoke rising gently from the chimney. The surrounding snow is untouched, soft and powdery, reflecting the pale, cool light of the overcast sky. The area around the cabin is empty, with just a few scattered snow-covered bushes and the distant outline of a forest at the edge of the field. The sky above is cloudy, casting soft, diffused light that creates long, gentle shadows on the snow, highlighting the textures of the frost and the simple lines of the cabin. The air feels crisp, and a few snowflakes are gently falling, adding to the tranquility. The image includes natural imperfections like a soft haze, slight lens blur in the distance, and fine details of snow drifts around the cabin, making it feel like a real, peaceful winter moment.

A serene landscape at golden hour, featuring rolling hills covered in lush green grass, a calm river reflecting the warm hues of the sunset, scattered wildflowers in the foreground, and a few fluffy clouds in a clear blue sky. The scene should capture the natural beauty and tranquility of the moment, with soft lighting and realistic textures, resembling a high-quality photograph.

Grok

Make a landscape picture.

Make a landscape picture.

Make a landscape picture.

Make a landscape picture.

Make a landscape picture.

Make a landscape picture.

Everyday People Category

Midjourney

A candid wedding moment of a couple at a wedding together under a canopy of leaves, evening reception vibe, the bride's flowing dress twirling as they dance, authentic emotions, photojournalistic style, high-resolution, sharp details, vibrant and warm tones, sony A7R

A vibrant street snapshot documentary style of two young women walking together in an urban park. They wear colorful, eclectic clothing with bold patterns and layered accessories, their hair dyed, and they carry unique bags and small items, capturing an alternative green background, documentary style, snapshot, dslr

A candid airport reunion scene, two people hugging deeply near the arrivals gate, one face visible slight tears, The busy terminal around them , with flight information screens and rolling luggage in the sharp background, handheld , documentary style, snapshot

Wedding photograph, unedited, couple walking down the aisle, people sitting on chairs blurry in the background, woman is smiling locking to the ground, men is lokking proud, in motion walking, sony a7R3

Dancers dancing on public square, surrounded by an audience of passersby some couples dancing closely, others laughing and spinning with flair. The square is paved with stones, framed by trees and historic buildings, sharp light, subtle colors Street photography, documentary style, sony, 50mm

public park in the distance a jogging middle aged man blue t shirt, exhausted look on face, sharp sunlight, documentary style, snapshot, 100mm, sony

photograph of an old white man, front view, portrait, closed eyes, full face, standing at the edge of a serene lake, gazing into the vast natural landscape, The man, wearing casual outdoor clothing, stands with a casual posture, amateur snapshot, 50mm, documentary style

Grok

a woman playing cello in a city, there are two people walking by. You can see a building in the background

a man reading a book. He is sitting on the stairs from a city church. The photo is taken from above, with a ray of light in his eyes.

A couple posing in front of the Eiffel Tower in Paris

a couple walking in a busy shopping street in Italy during the summer. They are a bit further away in the background and there is a tree, more in the front but to the side

two friends posing in front of a Christmas tree in a German Christmas market

A teenager skateboarding at a skate park with ramps and graffiti-covered walls in the background.

an old white man, standing at a lake. It is cloudy and you can see mountains in the background

someone dancing on the street. Other people are passing by and minding their own business. The person is wearing hip skater clothes

A construction worker operating machinery at a urban construction site during the day.

A cyclist riding along a scenic coastal road with the ocean and cliffs in the background.