Who Can Tell if it is AI? - Identifying Gender-Based Differences in AI Media Literacy

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Abstract

Artificial Intelligence (AI) is an increasingly embedded part of today's society and advances at a rapid pace. This steady improvement of AI's abilities makes it more difficult to distinguish real from artificial content. To study the people's ability to detect differences between AI-generated and human-made pictures, participants ($N = 192$) were randomly split into a training condition and a control condition and then completed online questionnaires and the main phase of the study. Results show no significant effect of the training condition but show an opposing effect when the image categories are considered separately: participants scored higher in correctly labelling AI as such, than labelling real photography correctly after training. Higher anxiety scores on AI-scales are positively related with the AI accuracy scores, but no such effect was found for the real image category. On average, women scored higher on accuracy than men. The study aims to increase the research-pool on AI-related topics and aims to spread awareness on potential threats that its development holds.

Keywords: Artificial Intelligence, AI, photography, AI anxiety, art

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Most of us have received or seen pictures made with the use of Artificial Intelligence (AI). Maybe your parents sent you an X post with funny pregnant cats or you watched an entertaining video on another social media platform. Maybe you have used ChatGPT to review an email or to improve academic work, simply to make your life easier. All these different instances seem like positive, or at least neutral, applications of AI. But this is not the only use of AI that is observable on the internet. Misuse of AI is becoming more apparent and its effects harsher as technology advances and AI systems are becoming widely available to not only qualified users, but the general public as well, allowing anyone access to its use. ChatGPT alone is widely used by professional and the public alike, in areas like everyday-research, as a communication tool, and the creation of content such as images (Kalla et al., 2023). With the steady improvement of AI generated pictures and videos, in 2017 a new category of pornography has developed: deepfakes (Gockel, 2024). According to the Cambridge Dictionary (2025) a deepfake is when a person's face or voice is replaced with that of another in a hyper realistic manner. In 2018, an application called FakeApp was released, allowing users to create deepfakes with minimal technical skills needed, and thus making the criminal use of AI publicly available (Meskys et al., 2020). Within a short period of time internet sites exclusively intended for deepfake pornography emerged and gained popularity (Karasavva & Noorbhai, 2021). Take the case of journalist Rana Ayyub in 2018. After sharing a social media post on violence against Muslims, a pornographic deepfake of her was released on the internet, which created an onslaught of sexist and violent threats towards the journalist (Bontcheva et al., 2023). Cases like these have only increased in relevance and gravity since 2018, as AI images are becoming progressively more accurate and harder to distinguish from real images (Gockel, 2024). More so than ever are women targeted by online revenge pornography which is seriously endangering women's mental health and safety, and additionally brings new challenges to lawmakers and lawyers (Darko, 2023). Not only pornography is created with the help of AI, but its use is extended to areas like politics, commercial work, and creative application (Meskys, 2020). To not fall for political propaganda, false advertisement, or mistakenly support artists using AI as a tool, learning how to distinguish real from artificially created content will become crucial for society as a whole. As people are more frequently exposed to AI content throughout their day-to-day lives, the issue of adequate AI media literacy comes to the foreground. It may be the case that people simply become better at identifying AI images as they become more exposed to them. Thus, the present research investigates whether mere exposure helps individuals distinguish real images from AI created ones, and whether certain individual characteristics make individuals more or less sensitive to it.

The study design used by Kornell and Bjork (2008) provides an effective framework for training individuals to distinguish AI-generated images from real ones. Their method of using an 'inductive learning' task, in which participants are exposed to multiple examples and later tested on distinguishing new, unseen images, closely aligns with this present research' method and goal to uncover if people can learn to detect AI more accurately. 'Inductive learning' describes learning through concrete examples which are then applied to other, similar scenarios (Kornell & Bjork, 2008). Specifically, through looking at example pictures of different artists, participants are expected to train their eyes to be able to distinguish different art styles more easily when later presented with different artwork. The focus here is to train an intrinsic process within the participants, meaning that detecting differences in the images comes naturally to the viewer (Kornell & Bjork, 2008). The present study applies the same logic to the concept of detecting AI-created images and presents the participants with artificial pictures. Within their study the researchers test 'interleaved practice' against 'massing practice' when detecting and distinguishing different artists' styles to see if one practice is more effective. The ‘interleaved practice’ paradigm is achieved through presenting the participants with multiple different art forms rather than teaching them one style at a time. They found that the interleaving technique leads to enhanced recognition, which provides a helpful base for the current research’ study design (Kornell & Bjork, 2008). Furthermore, using interleaved techniques additionally improved participant’s inductive learning abilities: they were more efficient in distinguishing different art styles. Applied to the current research, the same principle could be implemented to increase participants’ ability to detect the art style of artificially created images (Kang & Pashler, 2011).

Assuming that there are subtle differences in AI-generated images, individuals should be able to intrinsically learn to spot these differences through an interleaved inductive learning paradigm, which leads to the first hypothesis:

H1: Participants who undergo training in the form of an interleaved inductive learning paradigm will show higher accuracy in distinguishing between real and AI generated images compared to those without training.

If training does indeed improve peoples’ accuracy, this has practical applications for peoples’ awareness of AI usage in previously discussed fields like politics, commerce, and criminal cases. Untrustworthy campaign images, misleading commercial advertisements, and deepfake pornography could be identified more efficiently, thus reducing the spread of misinformation and mitigating potential societal and ethical harm.

This possibly harmful potential that AI holds is reason for scepticism for many individuals. It is further intensified as AI is increasingly integrated into the job market, replacing workers and automating processes that previously required human effort, subsequently increasing anxiety in possibly affected people (Huang et al., 2019). This concern could help individuals to detect AI content more efficiently, because situational anxiety has been shown to enhance attentional focus through redirecting cognitive resources on the threatening stimulus (Pacheco-Unguetti et al., 2010). This point is further supported by research suggesting that threat-related stimuli are detected quicker by people with higher anxiety levels, since their pattern recognition ability is increased when compared to non-anxious individuals (Bar-Haim et al., 2007). Additionally, a study on the effect of achievement anxiety on extrinsic and intrinsic motivation in language learning shows that a certain degree of anxiety acts as a facilitator and increases motivation to learn (Luo et al., 2020). Therefore, we speculate that a similar effect might be transferable onto the present study: through increased exposure to AI images in the training condition, the participants might feel more anxious to be fooled by AI and are thus more motivated to learn how to detect artificial imagery, in other words, to achieve a higher score in correctly labelling the shown photography. This theory is tested through the second hypothesis:

H2: AI-anxiety positively interacts with the training condition, which predicts better accuracy in detecting AI images.

In alignment with the findings above, heightened anxiety regarding privacy violation was found to be especially evident for women (Wang & Xiao, 2025). Additionally, women are anticipated to have higher anxiety levels about AI, given the previously discussed evidence that women statistically represent the demographic most affected by sexism-motivated online crimes (Gockel, 2024) and due to research suggesting that women generally have a higher prevalence of anxiety and higher scores on some anxiety related measures on average (McLean et al., 2011). Thus, the training condition might be more beneficial for women as it is assumed that their vigilance might help them differentiate images more easily with the added training, leading to the last hypotheses:

H3: Women will generally show higher accuracy in detecting AI images.

H4: Women will show higher scores on the anxiety scales.

Through applying these nuanced perspectives within the main concept that interleaved practice might teach participants to detect AI in a more effective manner, we strive to gain a more holistic view and a possible solution to the issue of undetected AI content in people's everyday lives.

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 to 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, one for ingenuine answers (acquiescence bias, also showing up as an influential outlier Cook's distance > 5), and one participant was excluded due to $n = 1$ for the third gender category not being a representative sample, for a final total of $n = 192$. Of the final sample, 71.35% were female ($n = 137$) and 28.65% were male ($n = 55$). 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 the purposes of 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 (1 = *‘strongly disagree’*, 7 = *‘strongly agree’*). A full list of items is in Appendix A. For an overview of descriptive statistics for each dimension see Table 1.

Furthermore, we made use of the Beck Anxiety Scale (Beck et al., 1988) to measure general anxiety in the participants.17 questions asked participants to self-assess how they felt within the last two months, including the current time, using a 4-point scale (0 = ‘*not at all*’, 3 = ‘*severely - I could barely stand it*’). 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 deleted 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, 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 A) 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 photograph 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 and 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 amount 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 for 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). The assumption check for equal variances was met, controlling with Levene's, $F(1,190) = 0.388$, $p = .534$ (see Table 9.)

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 $F(1,191) = 4.867\times10^{-4}$, $p = 0.982$ (see Table 10).

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 11), 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 12), 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 the IV. No significant interaction effect was found $F(3,192) = 0.835$, $p = .362$ (see Table 13).

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 14).

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 15). 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 15).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 16). 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 16).

Hypothesis 3

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 3 (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 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 17). To assess multicollinearity the VIF was assessed. A value larger than 10 was found for the interaction between Gender and Condition, suggesting severe multicollinearity (see Table 17).

Hypothesis 4

An independent sample T-test was run, to test hypothesis 4 (H4), 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 were found, $t(1.674)$, $p = .096$ (see Table 19).

Discussion

The general goal of the study was to test whether people can learn to detect differences between real and AI-generated photography after partaking in an interleaved learning process. Furthermore, we examined if AI-related anxiety might have a positive effect on participants in the training condition, making them more capable of accurately distinguishing between real and artificial pictures. We additionally included gender as a possible variable, investigating if there are differences between men and women in correctly identifying real and AI photography. Lastly, we analysed if gender may have an effect on AI-related anxiety scores.

Interpretation of Findings

Inspired by the interleaved learning paradigm being used to investigate if people can learn to distinguish different artists' styles (Kang & Pashler, 2011; Kornell & Bjork, 2008), we applied the same method to the AI-related context. Yet, we found no evidence for our first hypothesis, that participants of the interleaved training condition will be more accurate in distinguishing between the two image categories. Both participants who received training and those who did not had a 57.1% mean average accuracy, showing no significant effect of the training condition and proving that AI photography was difficult to be distinguished from real images. After further investigation, we did find an opposing effect: participants in the training condition labelled more AI-images correctly than they did real images, suggesting that participants felt more inclined to choose AI as a label for ambiguous photographs. This tendency may reflect a fear of being fooled by AI, rather than an increase in the ability to detect it, which is further highlighted by the almost 50/50 percent result in detecting images created by AI during the experiment. However, if fear of being actively fooled by AI is an accurate factor in this effect is not clear and sole speculation, as we did not include any measurements or scales in the present study to investigate this.

For the second hypothesis, we found no effect of AI-related anxiety scores on participants in the training condition, showing that people with anxious feelings towards AI who underwent the interleaved training did not generally improve in correctly labelling the shown images. Through further investigate the influence of AI-anxiety and the training condition in connection to the opposing effect found in H1, we discovered that higher AI-anxiety scores did in fact influence participants to have higher accuracy in labelling artificial photography correctly. This ties in with the previous argument that the fear of being deceived by AI could make people more sceptical of any viewed image and may heighten their attention. The increased exposure to potential AI content might have activated participants' state anxiety and increased their ability to detect artificial images more efficiently (Pacheco-Unguetti et al., 2010). However, again, this is an assumption not a tested fact.

To add further nuance, we included gender as a potentially influential variable in our third hypothesis and assumed that women will be better at detecting AI-images than men. We found that women on average had better accuracy in correctly labelling shown images during the main experiment. When adding the training condition as a variable in our analysis, we found no such effect and high chances of multicollinearity, showing that the training condition did not enhance women's ability in detecting artificial photography in contrast to men. It is probable that AI-related fears in specific are responsible for the found gender-related effect rather than general anxiety levels, because no gender difference was found when controlling for general anxiety levels in the sample. Women are frequently target of online-related crimes which are now enhanced through the emergence of AI (Bontcheva et al., 2023; Karasavva & Noorbhai, 2021), which possibly suggests that women are more vigilant when encountering media that is potentially artificially created. Social media platforms frequently sexualise women and female presenting bodies through their community guidelines, while allowing men and male presenting bodies to remain unrestricted. They police female bodies in a stricter manner, reinforce gender norms, and oversimplify gender identities, all without the viewer being fully aware nor autonomous (Gerrard & Thornham, 2020). This reality may increase women's inherent ability to detect AI images and leads to a baseline effect that may help explain why there was no gender-based differences after accounting for the training condition. With women already performing better at detecting AI-images through frequent exposure, the training might have had a higher benefit for men, which then evened out the accuracy in labelling the photographs correctly. This implies that the training condition leads to women plateauing in their performance, as it does not increase their predisposed ability to detect artificially created content, while improving men's skills. This assumption should be further investigated by future research.

Lastly, the fourth hypothesis tested if there are gender differences in AI-anxiety levels in the participants and assumed that women will have higher levels on average. This was shown to be correct after testing this assumption. This aligns with our previous findings of the third hypothesis, taking the above arguments into account in addition to research suggesting that women are the most frequent victim of sexism-related online crimes (Gockel, 2024) and might thus be more aware of AI's potential threat.

Strengths, Limitations And Future Research

While the present study provides useful insight into possible factors that influence the ability to detect AI, strengths and limitations must be considered before interpreting the findings. Similar to many other studies, this experiment was conducted on a sample group from a “WEIRD” sample, meaning its participants are mainly western, educated, from an industrialised, rich, and democratic country (Heinrich et al., 2010). This leads to lower external validity, as the sample cannot be generalised to a larger, more diverse population. Research suggests that collectivistic cultures have a different way of looking at pictures to analyse and understand them, and since the present research mainly studied Western Psychology students in The Netherlands, this type of research may be expanded to other, more collectivistic cultures to compare the effects (Alotaibi et al., 2017). Modern technology such as eye-tracking and heat maps could be used for effective differentiation. Additionally, the length of the study may have lead participants to be less concentrated while completing the study and they could have possibly been distracted through outside-stimuli, which could be controlled for in a laboratory-based experiment. On the other hand, requiring participants to travel to a specific location could possibly decrease the amount of participants that would be collected, as the experiment would then be less convenient to attend. Future research could test if the location of the experiment makes a difference in its results.

The study design itself creates a strong inner validity with participants being randomly assigned to a condition and the same pictures being used for every participant. The experimental nature of the project and the considerable sample size additionally strengthens the validity of the results. Yet currently there is little research on AI and its possible effects, because AI itself is a fairly new concept. As mentioned, AI technology steadily advances in its accuracy and ability to create deceivingly realistic content, making research quickly outdated. These points highlight the need for ongoing research that uses the newer editions of the AI systems to keep research up to date and close the research gap.

All things considered, the findings suggest that AI will become increasingly difficult to be detected in our daily lives, affecting many areas of the world and holding potential threat to general society. Thus, stronger regulations of AI are of utmost importance to prevent possible deception in areas like politics, commerce, or gender-related crimes as people grow less and less capable of distinguishing real from the artificial due to AI’s steadily advancing technology.

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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					

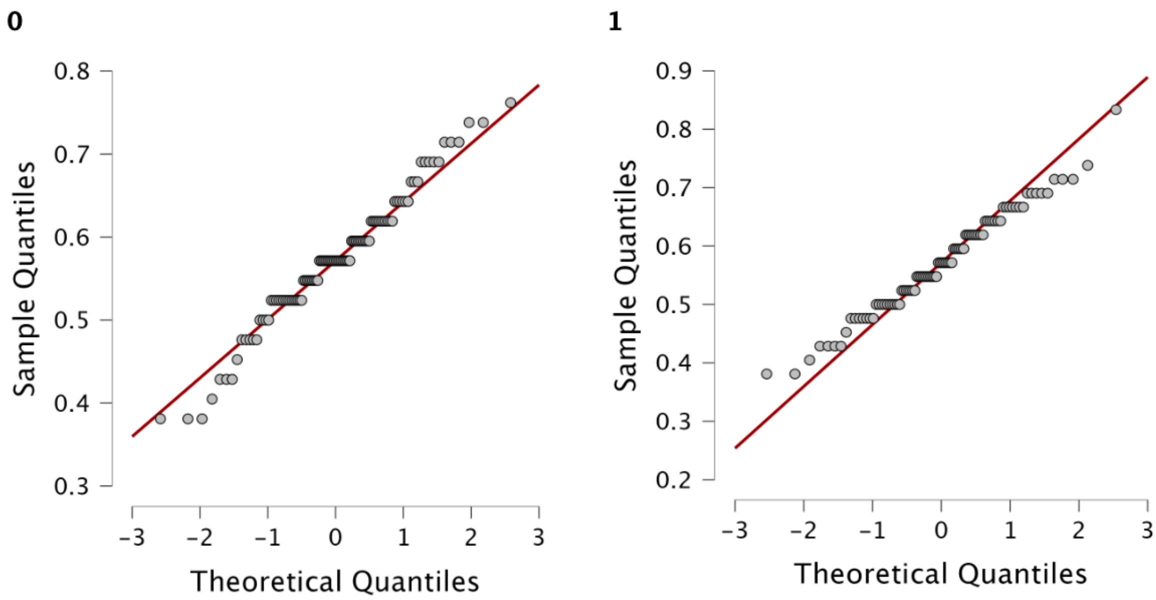
Beck Anxiety	Pearson Correlation	-.121	-.030	1				
	Sig. (2-tailed)	.094	.679					
	N	193	193	193				
AI Anxiety	Pearson Correlation	-.247**	-.058	.225**	1			
	Sig. (2-tailed)	<.001	.424	.002				
	N	193	193	193	193			
Real Accuracy	Pearson Correlation	-.074	-.394**	.050	-.023	1		
	Sig. (2-tailed)	.309	<.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	
Total_PercentCorrect	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

Test of Equality of Variances (Levene's)

	F	df_1	df_2	p
Total_Becks_Anx_Score	0.388	1	190	0.534

Table 10

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 11

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 12

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 13

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 14

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

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p	Collinearity Statistics	
							Tolerance	VIF
	AI Anxiety	8.044×10^{-4}	6.498×10^{-4}	0.135	1.238	0.217	0.442	2.262
	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 15

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		
	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 16

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

							Collinearity Statistics	
Model		Unstandardized	Standard Error	Standardized[a]	t	p	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 17

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		

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
	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
	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.

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.

Appendix A

Adapted Version: Beck Anxiety Inventory (BAI)

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

Appendix B

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.

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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 looking 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

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

ChurchReading: 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.

CoupleEiffel: A couple posing in front of the Eiffel Tower in Paris

CoupleWalkingItaly: 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

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

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

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

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

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

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