Computers in Human Behavior Reports 22 (2026) 101023

Contents lists available at ScienceDirect

Computers in Human Behavior Reports

journal homepage: www.sciencedirect.com/journal/computers-in-human-behavior-reports

Will people embrace AI art? Deconstructing psychological barriers in human appraisal of AI-labeled artworks

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ARTICLE INFO

Keywords:
Generative AI
Bias
Algorithm aversion
Creativity

ABSTRACT

Generative artificial intelligence (AI) possesses remarkable capabilities in producing diverse forms of human-like artistic creative content. However, based on the theoretical perspective of algorithm aversion in existing literature, it appears that people do not accord AI-generated works the same level of recognition as they do to human-created works. More importantly, the psychological mechanisms underlying this bias remain vague. Based on two pilot studies and five formal experiments (four were pre-registered), the present research systematically examined the "AI-label effect" and its psychological underpinnings. Our findings revealed a persistent evaluative bias against AI-generated artworks, moderated by four key mechanisms: individuals with more favorable attitudes towards AI exhibited mitigated bias (Study 1), perceived effort positively correlated with evaluative favorability (Study 2), existential threat perceptions induced by AI exacerbated bias (Study 3), and people paid less attention to the emotional aspects of AI paintings, which led to greater bias (Study 4). Notably, this bias diminishes when evaluative criteria shift from subjective artistic considerations to objective scientific parameters (Study 5). These insights advance our understanding of human–AI interaction dynamics by elucidating the cognitive architecture of algorithmic bias, while providing empirically grounded guidance for (a) developing AI systems that align with human evaluative frameworks, and (b) designing intervention strategies to mitigate perceptual asymmetries in human–AI collaboration.

1. Introduction

"*Can robots or AIs have human creativity?*" This question was among the 125 pivotal inquiries highlighted by the prestigious journal *Science* in 2021. Merely a year later, on November 30, 2022, ChatGPT was launched, and generative artificial intelligence (AI) officially entered people's life. This groundbreaking technology swiftly showcased its incredible capabilities to people, including in writing, chain-of-thought, and theory-of-mind tasks (Hagendorff, 2024; Noy & Zhang, 2023; Strachan et al., 2024). Recent evidence further indicated that generative AI has already shown a similar, or even better performance on a series of creative tasks than humans (Hitsuwari et al., 2022; Koivisto & Grassini, 2023; Orwig et al., 2024; Sun et al., 2025). Furthermore, it can assist people in creative tasks and enhance their creative performance (Doshi & Hauser, 2024; Lee & Chung, 2024; Vaccaro et al., 2024). As AI increasingly integrates into human creative activities, how do people perceive AI-generated creative products? Does bias arise simply owing to the AI label? If such bias exists, what factors drive it? These questions require systematic investigation.

From the perspective of algorithm aversion, individuals often exhibit irrational responses to algorithms, demonstrating a general preference for human output over algorithmic solutions (Dietvorst et al., 2015). For example, patients trust human doctors more than medical AI interventions (Longoni et al., 2020), and consumers rely more on the recommendations of friends rather than those of computer systems (Yeomans et al., 2019). Thus, a negative bias persists against generative AI even though it can provide substantial assistance across diverse tasks (Collins et al., 2024; Kung et al., 2023; Wan et al., 2024). Empirical studies indicate that individuals often express greater dissatisfaction when they are aware they are interacting with AI (Yin et al., 2024). This

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https://doi.org/10.1016/j.chbr.2026.101023
Received 6 November 2025; Received in revised form 28 February 2026; Accepted 17 March 2026
Available online 25 March 2026

phenomenon extends to the domain of creativity: while people struggle to differentiate between poems or paintings created by humans and those generated by AI, they exhibit a distinct aversion to works once they learn they are AI-generated (Bellaiche et al., 2023; Chiarella et al., 2022; Köbis & Mossink, 2021). This evidence supports the inference that people may have a negative bias towards AI-generated products. However, numerous previous experiments lacked controlled comparisons between human-produced and AI-generated works under identical conditions. Therefore, it remains challenging to isolate the specific impact of AI attribution on perceived creativity. More importantly, most of these studies merely discuss the phenomenon of bias against AI; empirical explanation of the underlying psychological mechanisms remains scarce. Thus, a critical question persists: what underlying factors derive this bias?

1.1. Negative attitude towards AI

Attitudes have a profound impact on human behavior (Ajzen, 1991; Ajzen & Fishbein, 1977). People's attitudes towards a given subject not only influence their behavioral tendencies but also shape their information selection and interpretation during cognitive processing. Currently, despite rapid advancements in AI technology, widespread concern and distrust towards AI remains (Young et al., 2021). Concerns regarding algorithmic opacity induce negative attitudes and suboptimal interaction experiences towards AI (Burrell, 2016; De Freitas et al., 2023; Pataranutaporn et al., 2023), which may establish a cognitive foundation for bias. Specifically, these negative attitudes may induce individuals to focus disproportionately on negative features and ignore objective evidence of quality or merit when evaluating AI-generated products. They may also exhibit confirmation bias, selectively attending to information that aligns with their pre-existing negative views (Nickerson, 1998). Consequently, such negative attitudes towards AI are likely to drive systematic evaluation biases against its outputs, including artworks.

1.2. Weak perceived effort of AI

Sometimes, the value of a matter lies not only in the outcome but also in the effort invested in the process (Inzlicht et al., 2018; Norton et al., 2012). Objects are accorded greater value when it is perceived that substantial effort has been invested in their creation. Effort confers value upon objects or outcomes, significantly impacting judgments, decision-making, and even beliefs regarding human creativity (Kruger et al., 2004; Zhang, A. et al., 2025). Lower perceived effort may lead to diminished quality assessment. This phenomenon may similarly manifest in AI-generated creative processes. The rapid response speed of AI could induce the perception that little effort has been invested in the creative process (Chamberlain et al., 2018). Moreover, individuals who utilize AI tools may be perceived as lazy and even experience mechanistic dehumanization (Dang & Liu, 2025; Zhou et al., 2025). Consequently, when individuals compare human-produced versus AI-generated products, they may intuitively perceive the latter as embodying less effort in their creation process. This cognitive bias likely leads to systematically lower quality perception and diminished value attribution towards AI-generated products.

1.3. Threat perception induced by AI

Sense of control represents a fundamental psychological need (Leotti et al., 2010; Ryan & Deci, 2000). Human behaviors across various everyday life scenarios (i.e., consumption) inherently require autonomous self-governance, which subsequently enhances subjective well-being (André et al., 2018; Wertenbroch et al., 2020). The loss of the sense of control can lead people to experience a series of adverse reactions (Shapiro et al., 1996). Recently, the accelerate development of AI has resulted in systems demonstrating substantial autonomous capabilities, achieving performance levels exceeding human capacities in specific fields (i.e., Orwig et al., 2024; Sun et al., 2025). This latent "substitution threat" is likely to trigger defensive psychological mechanisms (Kay et al., 2009), consequently generating resistance (i.e., preference for human-generated products despite comparable quality). In all, the perceived threat posed by AI may motivate negative evaluations as a means of maintaining human dominance on affected domains.

1.4. Greater emotional disengagement

Anthropomorphism also emphasizes that people usually project their mental states onto non-human subjects (Epley et al., 2007; Waytz et al., 2010). As for artistic or creative products, people tend to take emotional factors into account when evaluating them (Freedberg & Gallese, 2007; Graf & Landwehr, 2015; Köbis & Mossink, 2021). Therefore, there might be a prevailing expectation that art creators should constitute emotionally intelligent agents. However, AI systems are typically perceived as affectively deficient entities (Castelo et al., 2019). The integration of AI into human creative processes attenuates perceived interpersonal warmth and compromises interaction quality (Chen et al., 2025; Yam et al., 2025). This presumed "emotional deficit" may consequently activate evaluative biases, wherein AI-generated artworks are systematically perceived as incapable of eliciting genuine emotional resonance, ultimately receiving diminished appraisal. Emotional focus in appreciating artistic products may also induce a certain degree of bias. In other words, this emotional disengagement may shape people's bias when assessing AI-generated artworks.

1.5. Research overview

With generative AI increasingly permeating artistic creation and becoming an integral part of the contemporary art ecosystem (Bellaiche et al., 2023; Zhang, W et al., 2025), the appreciation of AI-labeled artworks is a topic worthy of scholarly attention. Art appreciation is a highly subjective and complex process, involving not only the content of the artwork itself but also contextual information surrounding its creation, such as human intention, emotion, and other related factors (Freedberg & Gallese, 2007; Graf & Landwehr, 2015). From the theoretical perspective of algorithm aversion (Dietvorst et al., 2015), individuals may exhibit systematic biases toward AI-generated outputs. However, the existence of such biases within the domain of art (like AI painting reproductions), as well as the underlying factors that drive them, requires further investigation.

The present research, which builds upon the aforementioned research landscape and focuses on AI-labeled paintings, is designed to address the following two core objectives: (1) to establish the existence of bias against artworks labeled as AI-generated, and (2) to elucidate the underlying factors contributing to this bias. Guided by these research objectives, we conducted a systematic investigation comprising two pilot studies and five formal studies (four were pre-registered). Table 1 presents the overall architecture of the studies conducted throughout this study. The whole research was reviewed and approved by the University Committee on Human Research Protection of East China Normal University with the approval number: HR2-0262-2024, dated December 5, 2024.

To ensure that the lower evaluations of AI artworks stem solely from the AI label rather than the artworks' intrinsic attributes, and none of the participants has previously seen the paintings, all materials in the present research were AI-generated (including those labeled as human-created in the formal experimental conditions). This design effectively controls for potential quality differences between a human-created and an AI-generated artistic production. Pilot Study 1 was conducted to generate stimulus materials using AI tools (GPT-4, Artbreeder), with 30 participants recruited for initial screening to select suitable materials for subsequent studies. Pilot Study 2 was designed to obtain objective, label-free ratings of the stimulus materials. Participants rated the materials

Table 1
Overview of studies.

Study	Pre-registration	Sample size	Purposes
Pilot study 1	null	$N = 30$	Generating artworks using AI tools and conducting initial screening to select materials for the subsequent formal studies.
Pilot study 2	null	$N = 62$	Obtaining objective ratings (without labels) of the materials for robustness check in the subsequent formal studies.
Study 1	null	$N = 60$	Confirming the existence of "AI-label effect" phenomenon and examining the influence of attitudes toward AI.
Study 2	https://aspredicted.org/q7sx-wyfw.pdf	$N = 60$	Examining the influence of perceived effort on bias toward AI-labeled artworks.
Study 3	https://aspredicted.org/s8hr-tcvf.pdf	$N = 120$	Examining the influence of perceived threat on bias toward AI-labeled artworks.
Study 4	https://aspredicted.org/np8s-qssv.pdf	$N = 85$	Examining the influence of emotional engagement on bias toward AI-labeled artworks.
Study 5	https://aspredicted.org/5jbv-y3ck.pdf	$N = 102$	Examining the consistency of bias effects toward AI-labeled works across different types of tasks.

that would later be assigned AI or human labels in the main experiments, but did so without any labels attached. The label-free rating data collected were then utilized for reliability assessment in the subsequent formal studies.

2. Study 1

Study 1 focused on the phenomenological level, aiming to reveal the existence of evaluative bias towards AI-generated artwork and examine how attitudes towards AI influence this bias.

2.1. Participants

We recruited 60 participants ($M_{age} = 20.97 \pm 2.04$ years; 38 females, 22 males) through campus social media groups. All participants identified as Chinese (with one ethnic minority). All participants completed the informed consent procedure before the formal experiment. Given the study's requirement for art appreciation, we ensured participants were non-art majors with normal color vision and visual acuity. The sensitivity power analysis using G-power (Faul et al., 2007) indicated that the sample size would provide 80% power to detect an effect of $dz = 0.37$ with $\alpha = .05$ in the present experimental design.

2.2. Procedure

First, the Attitudes towards artificial intelligence Scale (ATTARI-12, Stein et al., 2024) was used to measure individuals' attitudes towards AI across three dimensions: cognition, behavior, and affect. It comprises 12 items (e.g., AI will make this world a better place). Participants were required to rate each item on a 5-point scale (from 1 = totally disagree to 5 = totally agree). In this study, the scale demonstrated acceptable reliability (Cronbach's $\alpha = .80$).

Study 1 implemented a within-subject design. In the experiment, participants were required to rate 80 paintings (from pilot studies). The ratings addressed four dimensions: creativity (*how creative you think this painting is*), aesthetics (*how much aesthetic value you think this painting can bring*), degree of liking (*how much you like this painting*), and degree of delicacy (*how refined you think this painting is*). Participants had to rate on a scale of 1–9 (1 representing "dislike very much" and 9 representing "like very much"). The rating procedure was implemented via keyboard input. Three practice trials were held to ensure participants' familiarity with the formal experimental procedure. In the formal 80 trials, the 80 paintings obtained from Pilot Study 1 was randomly divided into two groups with two labels. In 40 trials, the label "Created by AI" was presented when the painting was shown; in the other 40 trials, the label "Created by Human" was presented. It is noteworthy that the pairing between each painting and its assigned label was fixed throughout the experiment (each painting was associated with only one label). This pseudo-randomized design was implemented to enable the referencing of label-free ratings obtained in Pilot Study 2, which would be applied for robustness check in the subsequent statistical analysis. To render the stimuli more realistic, in the "Created by Human" labels, we randomly generated 40 different virtual names and placed them in the labels (e.g., "Painted by Sabrika"; See Fig. 1A). In each trial, participants were provided sufficient time to appreciate the painting and thereafter rate the painting by pressing keys. The presentation order of stimuli from the two conditions was fully randomized. The experimental tasks were performed in an offline laboratory, and the stimulus materials were presented through the E-Prime program. Upon completion of the experiment, participants received CNY 20 as compensation.

2.3. Results

We conducted four separate t-tests on the four dimensions with the label being independent variable. The results showed that the participants had a more positive evaluation of the paintings with the label, "Created by human." Fig. 1B displays the differences between the two labels. Participants believed that the paintings by humans were more creative ($t_{(59)} = 3.40$, $p = .001$, $d = 0.63$), had higher aesthetic value ($t_{(59)} = 5.03$, $p < .001$, $d = 0.92$) and delicacy ($t_{(59)} = 4.47$, $p < .001$, $d = 0.81$), and they liked the paintings created by humans better ($t_{(59)} = 3.96$, $p < .001$, $d = 0.73$, see *SI Appendix* Table S1 for specific statistical indicators). To ensure that the differences in evaluations stemmed from the labels rather than the paintings themselves, we conducted corresponding analyses on the ratings of unlabeled paintings in Pilot Study 2 based on the grouping in this study. The results showed that there were no significant differences in all dimensions (see Table 2). The above results indicates that when people know that an artistic creative product is AI-generated, they show a negative bias towards it, according it lower evaluation.

To examine the effect of the priming attitude on participants' bias towards AI, we obtained the *Bias* index for each participant by subtracting the mean ratings given by each participant to all paintings labeled as "Created by AI" from the mean ratings given to all paintings labeled as "Created by human" in Study 1. It is expressed as:

$$\boldsymbol{Bias} = \frac{1}{n}\sum_{1}^{n}\boldsymbol{R}_{human} - \frac{1}{n}\sum_{1}^{n}\boldsymbol{R}_{AI}$$

Where n denotes the number of trials, R_{human} denotes the ratings given to the paintings labeled as "Created by human" in specific trial and R_{AI} denotes the ratings given to the paintings labeled as "Created by AI" in specific trial. The larger the calculated value, the greater the bias of the participants against AI labeled work. A series of linear regression analysis was conducted to predict the bias in each of the four main dependent variables. The predictors were participants' attitudes towards AI (detail in Methods section). The results showed that attitude towards AI can significantly predict the bias towards AI paintings (see visualization in Fig. 1C and test statistics in *SI Appendix* Table S2). When attitude towards AI becomes more positive, the bias towards AI paintings in all four dimensions of evaluation will decrease.

3. Study 2

Study 2 aimed to further validate the existence of bias and investigate the role of perceived effort. Specifically, whether participants' bias

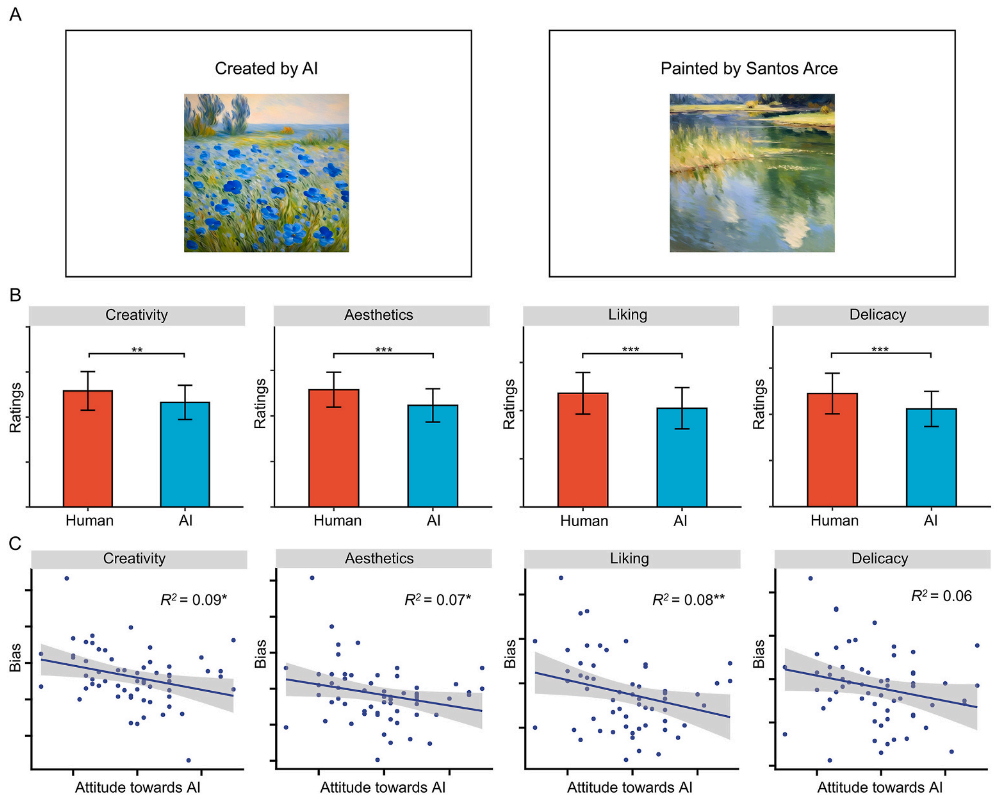

Fig. 1. (A) Schematic illustration of the presentation format for image stimuli under the two labeling conditions in the experiment. (B) The differences between the ratings of Human label and AI label. (C) The effect of attitude towards AI on people's bias towards AI. Note, the error bars represent the standard deviation; $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2
Results of robustness check for Study 1.

	Ratings ($M \pm SD$)		t	p	Cohen's d
	Human	AI			
Creativity	6.02 ± 0.95	6.08 ± 1.11	0.28	0.778	0.06
Aesthetics	5.99 ± 0.93	6.05 ± 0.92	0.27	0.781	0.06
Liking	5.45 ± 1.06	5.50 ± 1.07	0.20	0.842	0.05
Delicacy	5.67 ± 1.10	5.75 ± 0.95	0.36	0.717	0.08

against AI-generated artworks stems from their perception of inadequate effort exerted by AI. Study 2 was pre-registered at https://aspredicted.org/q7sx-wyfw.pdf.

3.1. Participants

In accordance with the pre-registered sample size, we recruited 60 participants (M_{age} = 22.25 ± 2.26 years; 43 females and 17 males) through campus social media groups. The sample size meets the pre-registration requirements. All participants identified as Chinese. All participants completed the informed consent procedure before the formal experiment. Study 2 employed the same participant exclusion criteria as in Study 1. The sensitivity power analysis indicated that the sample size would provide 80% power to detect an effect of $f = 0.17$ with $\alpha = .05$ in the present experimental design.

3.2. Procedure

Study 2 utilized a within-subject design (with three conditions). In this study, participants were required to rate 78 paintings (from pilot studies, 26 for each condition). The ratings covered four dimensions: creativity, aesthetic, liking, and delicacy (same as in Study 1). Before commencing the experiment, participants were presented with the following instructions:

> "An AI company dedicated to image generation has invested **500 million yuan** and spent **four years** developing an enhanced large-model named SuperPainter specifically for painting creation. This model is different from other AI tools on the market. When a user enters a drawing instruction, SuperPainter usually takes **30–40 minutes** to generate the final painting by **calling multiple built-in sub-models and other tools**. You are now participating in the product test of this tool. Next, you will be presented with a series of paintings from human artists, ordinary drawing AIs, and SuperPainter. You need to rate them from four dimensions respectively."

Subsequently, participants completed 78 trials (26 for "*human artist*" label, 26 for "*ordinary AI*" label, 26 for "*SuperPainter*" label). The presentation order of trials across different conditions was randomized. Each painting was displayed simultaneously with its associated label, ensuring participants were aware of the designated creator of the artwork. After completing the rating task, participants were also required to complete a ranking question to examine their perceived effort: *How much effort do you think the three creators put into their creations?* This question was adapted from established practices in prior research and ranking tasks are recognized as an effective method for validating manipulations across three levels (Gerstenberg & Lagnado, 2012; McCoy & Ullman, 2019). The experimental tasks were performed in an offline laboratory, and the stimulus materials were presented through an online program (www.wjx.cn). After the experiment, the experiment purpose was re-explained to the participants and CNY 20 were provided as compensation to each of them.

3.3. Results

A Friedman test was conducted on the manipulation check (as the manipulation check question was a ranking question, the obtained data represent categorical variables), revealing a main effect of the manipulation ($\chi^2 = 79.63$; $p < .001$, effect size $W = 0.66$). Participants believed that humans invested the greatest effort when painting, followed by the SuperPainter, while the ordinary AI put in the least effort. Thereafter, a series of ANOVAs were conducted on the manipulation check and four main dependent variables. Fig. 2 illustrates the differences of ratings among human, AI, and SuperPainter conditions. There were significant main effects of labels on all four evaluation dimensions. Paintings labeled as "Created by human" were always regarded as having the highest levels of creativity ($F_{(2, 118)} = 10.45$, $p < .001$, $\eta^2 = 0.11$), aesthetics ($F_{(2, 118)} = 14.89$, $p < .001$, $\eta^2 = 0.14$), and delicacy ($F_{(2, 118)} = 13.62$, $p < .001$, $\eta^2 = 0.13$). Participants also liked them the most ($F_{(2, 118)} = 12.15$, $p < .001$, $\eta^2 = 0.12$). Compared with those labeled as "Created by ordinary AI," paintings labeled as "Created by SuperPainter" were also considered to embody greater creativity, aesthetics, and delicacy. But there was no significant difference in participants' preference for paintings labeled with "Created by ordinary AI" and "Created by SuperPainter" (see *SI Appendix* Table S5-S6 for specific statistical indicators). The above results suggest that people have a more positive evaluation of creators who are perceived to have invested significant effort. To further verify the reliability of the conclusion, we grouped the unlabeled scores in Pilot Study 2 according to the three corresponding labels for analysis. The results showed no significant differences between groups in all dimensions (see Table 3). This indicted that the differences between groups in Study 2 stem from labels rather than the paintings themselves.

4. Study 3

Study 3 focused on perceived threat, building upon established bias effects to investigate how varying levels of AI-induced threat influence individuals' biases against AI. Study 3 was pre-registered at https://aspredicted.org/s8hr-tcvf.pdf.

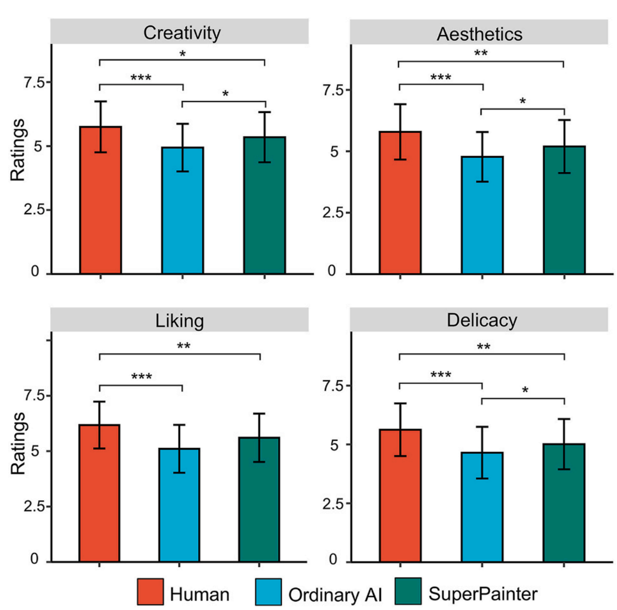

Fig. 2. The differences among the ratings of Human label, Ordinary AI label, and SuperPainter label. Note, the error bars represent the standard deviation; *$p < .05$, **$p < .01$, ***$p < .001$.

Table 3
Results of robustness check for Study 2.

	F	p	η^2
Creativity	0.56	0.576	0.014
Aesthetics	0.53	0.592	0.014
Liking	0.92	0.400	0.024
Delicacy	0.008	0.992	0.000

4.1. Participants

We recruited 120 participants ($M_{age} = 20.80 \pm 2.06$ years; 78 females and 42 males) in Study 3. All participants identified as Chinese (with four identifying as ethnic minority). Owing to an oversight that the recruitment was not stopped immediately upon reaching the pre-registered target of 100 participants, the actual sample size slightly exceeded the pre-registered number. A sensitivity power analysis indicated that the sample size would provide 80% power to detect an effect of $dz = 0.51$ with $\alpha = .05$ in the present experimental design. The results of this post-hoc sensitivity analysis also confirm that the statistical power remains adequate with the actual sample size. All participants completed the informed consent procedure before the formal experiment. The recruitment methods and exclusion criteria were identical to those employed in the two previous experiments.

4.2. Procedure

Study 3 adopted a between-subject design. All participants in this study were randomly divided into two groups: a control group and a threat group. Participants in the two groups were presented with different instructions before the task. Participants in the control group read the following instructions:

> "Generative AI is widely used in the field of artistic creation. A professional illustration-drawing company is considering purchasing membership accounts for a highly advanced painting AI model for its professional artist employees to **assist** them in their work. If the AI model proves to be effective, the artist employees' **work pressure will be significantly reduced**, and work efficiency will be improved. Next, please conduct a user evaluation. You need to choose the better one from the two paintings presented in each round."
>
> Participants in the threat group read the following instructions:
>
> "Generative AI is widely used in the field of artistic creation. A professional illustration-drawing company is considering purchasing an expensive painting AI model to **replace** their own professional artist employees. If the model demonstrates good performance, the company will consider **reducing the number of professional artist employee** and having the AI model undertake the primary work, thus saving operational costs. Next, you will be conducting a user evaluation. You need to choose the better one from the two paintings presented in each round."

Next, participants in both groups were required to finish a 40-round selection task (a total of 80 paintings, same as in Study 1, and each painting was consistently assigned a label identical to that used in Study 1, allowing for subsequent reliability checks by referencing its label-free ratings from Study 2). Notably, we replaced the rating paradigm with a forced-choice paradigm. This modification aimed to replicate the findings under different methodological frameworks to ensure the robustness of our conclusions. Additionally, the forced choice paradigm has demonstrated superior validity in attitude measurement research (Knowles & Condon, 1999; Paulhus, 1991). In each round, two paintings were presented. One was labeled as "*painted by company employees*" and the other as "*created by AI.*" The pairing of paintings with the two labels within each trial was randomized. Paintings associated with the two label conditions were randomly presented on either the left or right side of the screen, with the presentation positions counterbalanced. Participants were required to make four choices: *Which one is more creative?; Which one is more aesthetic?; Which one do you prefer?;* and *Which one is more delicate*? The experimental task was performed in an offline laboratory. The instructions and the painting works were presented directly on paper materials, so as to render the "user evaluation" scenario more realistic. After completing the selection task, participants had to answer two questions about the sense of threat for the manipulation check: *To what extent do you think AI tools are likely to replace humans?; How concerned are you about this?* After the experiment, we explained the true intention of the experiment to the participants again. Each participant received CNY 20 as compensation.

4.3. Results

Results of manipulation check showed that participants in the threat group more frequently expressed fear and concern about being replaced and controlled by AI (see *SI Appendix* Table S7 for test statistics). The results of participants' choices indicated that the participants in the control group were more likely to consider paintings with AI labels to be more creative ($t_{(118)} = 5.85$, $p < .001$, $d = 1.04$), aesthetic ($t_{(118)} = 2.49$, $p = .014$, $d = 0.48$) and delicate ($t_{(118)} = 5.04$, $p < .001$, $d = 0.90$) than those in the threat group, and they also showed a greater preference for AI-paintings ($t_{(118)} = 6.86$, $p < .001$, $d = 1.26$, see visualization in Fig. 3 and test statistics in *SI Appendix* Table S8). Additionally, regardless of whether it was under the control condition or the threat condition, the proportion of people choosing the human label was higher than that of choosing AI label (see *SI Appendix* Table S9 for test statistics). These results suggest that in the context of the forced-choice task, bias against AI persisted. Moreover, this bias intensified when people perceived the threat posed by AI.

5. Study 4

Study 4 examined emotional factors, investigating how differential attention to artwork attributes (objective technique vs. subjective emotion) modulates bias against AI-generated paintings. Study 4 was pre-registered at https://aspredicted.org/np8s-qssv.pdf. Notably, we conducted additional exploratory analyses in Study 4 that were not included in the pre-registration. These modifications were strictly limited to analytical approaches and did not involve any alterations to the original experimental design.

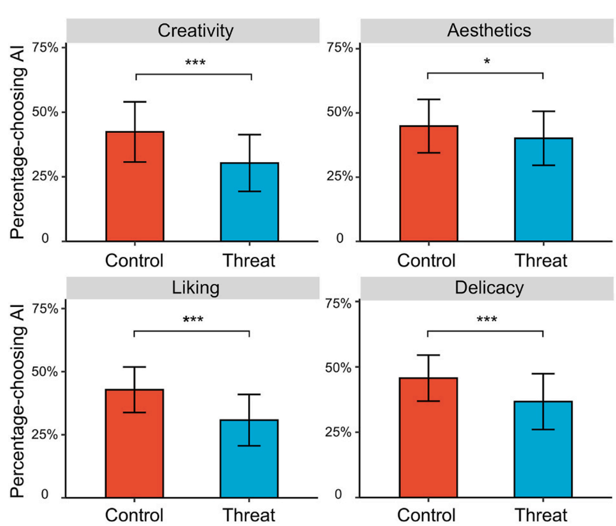

Fig. 3. The differences in selection rates under Control condition and Threat condition. Note, the error bars represent the standard deviation; *$p < .05$, ***$p < .001$.

5.1. Participants

In accordance with the pre-registered sample size, we recruited 85 participants ($M_{age} = 21.48 \pm 2.19$ years; 52 females and 33 males) through campus social media groups. The sample size meets the pre-registration requirements. All participants identified as Chinese. All participants completed the informed consent procedure before the formal experiment. Same exclusion criteria were applied in this study as in the previous studies. The sensitivity power analysis indicated that the sample size would provide 80% power to detect an effect of $dz = 0.61$ with $\alpha = .05$ in the present experimental design.

5.2. Procedure

Study 4 also adopted a between-subject design. In this experiment, participants were randomly divided into two groups. One group of participants was asked to pay more attention to the story and emotions of the paintings ("*please envision the scene depicted in this painting and its narrative context. Contemplate the emotions conveyed by its visual elements and engage with the artwork through personal reflection*") in the subsequent tasks (the emotion group, $n = 42$), while the other group was required to focus more on the techniques and details ("*please focus on the color palette, compositional structure, and evaluate the painting from objective perspectives such as texture, interplay of light and shadow, and brushstroke technique*") of the paintings (the detail group, $n = 43$). Next, participants in both groups were required to complete a 30-round painting evaluation task (the materials are from the pilot studies, with 15 rounds labeled as "*created by AI*" and 15 rounds labeled as "*created by human*"). As this study investigated the emotional factors of paintings, more emotional indicators were measured. In each trial, participants first had to rate the painting on a scale of 1–7 from three holistic dimensions: aesthetics, profundity, and creativity. Subsequently, they had to rate the painting on a scale of 1–7 from 10 different aesthetic emotion dimensions: liking, awe, enchantment, joy, vitality, interest, insight, uneasiness, boredom, and sadness. These 10 emotions were selected from previous studies on aesthetic emotions in paintings (Schindler et al., 2017). Next, participants were required to evaluate the emotional perception induced by the painting from two overall dimensions: valence (from 1 being very negative to 7 being very positive) and arousal (from 1 being very calm to 7 being very intense). Finally, participants had to report their focus on the painting in this trial of the task (from 1 being completely unconcerned about the emotional expression of the painting to 7 being highly concerned about the emotional expression of the painting). Owing to the multiplicity of evaluation dimensions and the relatively extended duration of the experiment, we set up only 30 trials in this study to avoid participation fatigue. The experimental task was performed in an offline laboratory, and the stimulus materials were presented through the E-Prime program. Upon completion of the experiment, participants received CNY 20 as compensation.

5.3. Results

Unexpectedly, the results of manipulation check were not significant. There were no between-group differences in the participants' points of attention (see *SI Appendix* Table S10 for test statistics). However, participants' focus was influenced by the labels ($t_{(83)} = 7.66$, $p < .001$, $d = 0.59$). The results showed that the participants paid more attention to emotions when it came to the paintings labeled as "Created by human" (see *SI Appendix* Table S13 for test statistics). Consequently, we conducted additional exploratory analyses beyond our pre-registered protocol.

Next, taking the label as the independent variable, a series of t-tests was conducted on all the evaluation dimensions. The results showed that on the dimension of positive emotions, people accorded higher evaluations to the works with the label "Created by human." Conversely, on the dimension of negative emotions, people gave higher ratings to the works with the label "Created by AI" (see visualization in Fig. 4A and test statistics in *SI Appendix* Table S13). Furthermore, as an exploratory analyses approach, we took the label as the independent variable, the manipulation check ratings as the mediating variable, and the evaluation as the dependent variable to conduct a mediation analysis. The results showed that people accorded greater attention to the emotions of the paintings because of the human label, and, consequently, gave them higher evaluations (see visualization in Fig. 4B and test statistics in *SI Appendix* Table S14~S15). The above results further verified the robustness of the bias towards AI paintings and revealed that such bias may stem from the differences in the emotional focus on AI works.

6. Study 5

The previous four studies consistently focused on artistic creations, elucidating the underlying causes of evaluation bias towards AI products from attitudinal, cognitive, and affective dimensions. Study 5 shifted the stimulus modality from paintings to textual materials (from artistic creative products to scientific creative products), examining whether such bias demonstrates cross-task consistency. It was pre-registered at https://aspredicted.org/5jbv-y3ck.pdf.

6.1. Participants

According to the pre-registered sample size, we recruited 102 participants ($M_{age} = 20.53 \pm 1.80$ years; 59 females and 43 males) through campus social media groups. The sample size meets the pre-registration requirements. All participants identified as Chinese (with two ethnic minority). All participants completed the informed consent procedure before the formal experiment. The sensitivity power analysis indicated that the sample size would provide 80% power to detect an effect of $f = 0.33$ with $\alpha = .05$ in the present experimental design.

6.2. Procedure

In this study, the Scientific Divergent Application Task (SDAT; Wan et al., 2025) was applied. We presented a series of new scientific materials and introduced the characteristics of these materials. Subsequently, we showed a series of potential applications of these materials. Notably, all the potential applications were generated in the previous research (Wan et al., 2025). A possible example is as follows:

> *Resin is a two-component liquid. It has characteristics such as high transparency, good elasticity and flexibility, being difficult to break, not turning yellow, and having good water-locking properties. What occasions might this material be used for? Possible applications include: making belts, due to its good flexibility and low breakage tendency; preserving fresh flowers, due to its transparency and good water-locking properties* (see detailed materials in *SI Appendix*).

Study 5 utilized a mixed design. Participants were randomly divided into two groups: the control group and the experimental group. Participants in both groups were required to rate 60 uses of 10 materials (six uses for each material). The ratings were conducted for two dimensions: novelty (*how novel you think this use is*) and usefulness (*how useful you think this use is*). Participants were required to rate these two dimensions on a 5-point scale (i.e., 1 representing "not novel at all" and 5 representing "extremely novel"). Participants in the control group were directly presented with 60 items and then asked to rate them without labeling—they were not informed whether these items were created by humans or generated by AI. Participants in the experimental group were informed that 30 of the uses were AI-generated and the other 30 were proposed by previous participants (for each material, three uses were labeled as AI-generated and three as human-proposed). The experimental tasks were performed in an offline laboratory, and the materials were presented through an online program (www.wjx.cn). After the experiment, we explained the purpose of the experiment to the participants in the experimental group. All participants received CNY 10 as compensation.

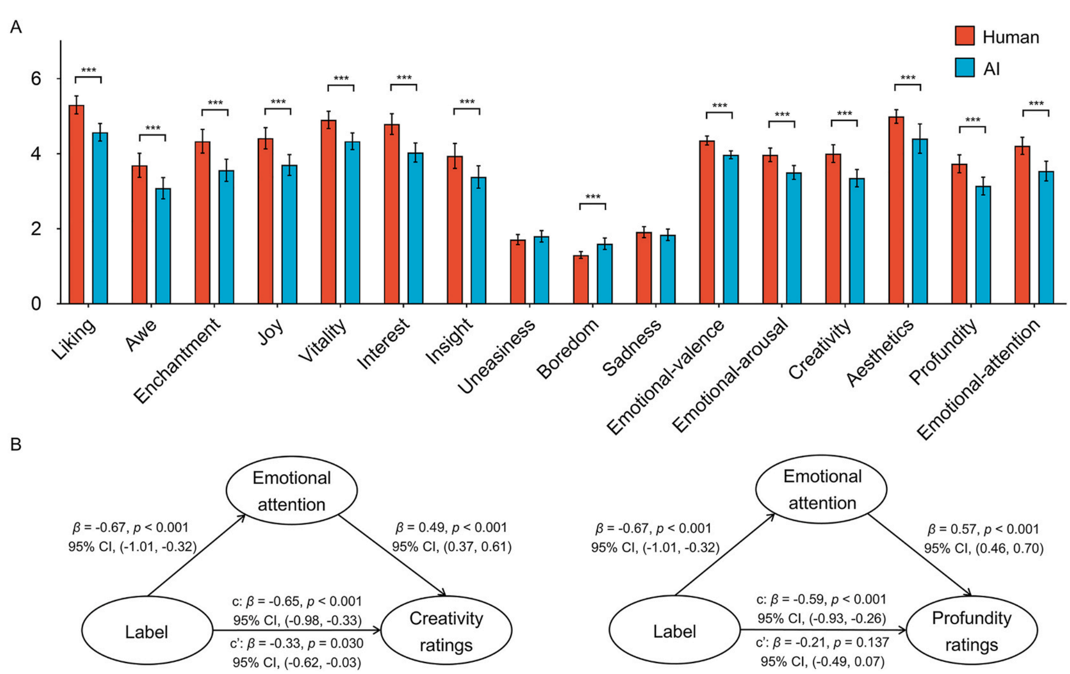

Fig. 4. (A) The differences between the ratings of Human label and AI label. (B) The results of the mediation models. Path β denotes standard coefficient, path c denotes the total effect, and path c' denotes the direct effect. Note, the error bars represent the standard error; *$p < .05$, **$p < .01$.

6.3. Results

The results showed that there were no significant differences in the ratings of these uses by the two groups of participants on the two dimensions (novelty and usefulness). The main effect of condition ($p = .80$ for novelty dimension and $p = .99$ for usefulness dimension) and the main effect of label ($p = .15$ for novelty dimension and $p = .23$ for usefulness dimension) were not significant. Participants in the with-label group also showed no significant differences in their ratings between the "human-generated" label and "AI-generated" label (see visualization in Fig. 5 and test statistics in *SI Appendix* Table S17-S18). In addition to significance testing, we applied Bayesian analyses to provide evidence supporting the null hypothesis through Bayes factors using JASP software (Wagenmakers et al., 2018). The results showed that for participants in the experimental group, their ratings of human-labeling versus AI-labeling on the novelty dimension yielded $BF_{10} = 0.55$, while on the usefulness dimension, $BF_{10} = 0.19$. These findings further support the non-significant results of the frequentist t-tests, providing weak to moderate evidence in favor of the null hypothesis. Integrating the results from both ANOVA and Bayesian factor analyses indicates that, under the current experimental design and with the present participant sample, no significant bias against AI-generated scientific creativity products was observed. This finding contrasts with the bias detected towards AI-generated artistic products in previous four studies. This discrepancy suggests that the type of task may influence people's attitudes towards AI-generated outputs.

7. Discussion

Despite the remarkable capabilities of present-day AI, people continue to exhibit biases against it. The present research employed a multi-experiment, cross-paradigm, and cross-task framework to repeatedly examine the AI labeling effect and clarify its underlying influencing factors. Study 1 revealed the existence of bias against AI through the "label effect," demonstrating that evaluations of paintings were influenced by whether they were attributed to AI or humans. Additionally, the results indicated that individuals with greater positive attitude towards AI exhibited less bias. Studies 2 to 4 further investigated the underlying causes of this bias, identifying three key factors: lower perceived effort invested by AI, a sense of threat posed by AI's autonomy, and the belief that AI lacks emotional capacity. Moreover, Study 5 showed that the bias could be mitigated by altering the type of task or stimulus materials, suggesting that the bias against AI is context-dependent and influenced by the nature of the task.

Overall, the findings of this research align with those of previous studies and recent investigations into generative AI, but crucially, our work provides consistent and robust evidence across multiple experiments to demonstrate the persistence of human biases against AI (Dietvorst et al., 2015; Chiarella et al., 2022; Zhang, W et al., 2025). However, given that this study focuses on creative tasks, the observed negative bias may not be solely attributable to a perceptual error driven by algorithm aversion. It might also reflect an appreciation among human participants for the distinctiveness of human creative cognition. The contrast between these two sources could explain the differences in evaluation outcomes. Study 2 revealed that attributing the quality of "effort" to AI significantly reduced people's bias towards it. This mirrors the "effort preference" observed in daily social interactions, where individuals tend to evaluate those who demonstrate hard work more positively (Muenks et al., 2016). Our study extends this "effort preference" to the domain of AI, suggesting that when people perceive AI as investing substantial effort to complete tasks, they are more likely to attribute human-like positive qualities to it, leading to more favorable evaluations. This indicates that human interactions with AI are not solely based on its technical attributes; rather, people apply cognitive patterns typically used for human behavior to AI, imbuing it with "human-like" characteristics.

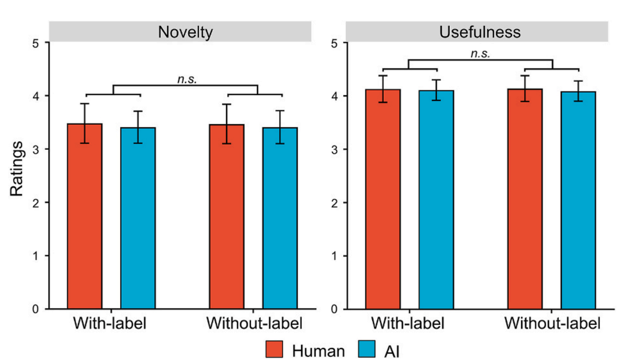

Fig. 5. The differences among the four conditions. For the bars of "without label" group, the red bar indicated the items which were labeled "generated by human" in the "with label" group. The blue bar indicated the items which were labeled "generated by AI" in the "with label" group. Note, the error bars represent the standard deviation; "*n.s.*" denotes nonsignificant. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

People's bias towards AI intensified when feeling threatened (in Study 3), which may reflect humans' rejection of out-group (Fiske et al., 2002). This further indicates that people might have come to view AI as a parallel existence to humans, rather than simply a tool or a machine. The belief that regards AI as an intelligent agent similar to humans, instead of a tool, elicits greater concern—even fear, thus exacerbating bias. This kind of bias, serving as a cognitive shortcut, assists individuals in making rapid judgments when confronted with potential threats, thereby safeguarding their psychological and social interests. This further corroborates the profound influence of emotional and motivational factors on information processing and attitude formation during human cognitive process. From the perspective of the Technology Acceptance Model (Davis, 1989), perceived threat might also be an important factor influencing users' attitudes towards AI. In the measurement of attitudes towards AI, the fear of being threatened or replaced by AI is a source of negative attitudes. This also corresponds to the results of Study 1, where negative attitudes towards AI significantly induced biases.

Does AI have emotions? From a psychological perspective, our research demonstrates that, regardless of whether AI itself has emotions, humans currently still perceive it as lacking in emotions. In the context of aesthetics, emotional resonance is considered a pivotal element (Leder et al., 2004; Silvia, 2005). Painting, as a medium of artistic expression, inherently carries profound emotional connotations. Audiences are accustomed to seeking the emotional imprints of artists within their works. In Study 4, when participants were presented with AI-generated paintings, the perceived absence of "human-label emotions" led to negative evaluations rooted in the bias of "emotional deficiency." This underscores the central role of emotional factors in shaping human aesthetic judgments of AI-generated art and highlights a persistent preference for human-led creation. Conversely, within the realm of scientific materials, objectivity is prioritized (Kuhn, 1962). In Study 5, we indeed did not observe a significant AI-label bias. This suggests that the inherent differences between artistic and scientific materials may subtly influence the criteria people apply to evaluate them. Specifically, individuals may prioritize subjective experience and a perception of "human-like" quality in artistic tasks, leading to a negative bias against non-human creators. Conversely, scientific tasks emphasize objective outcomes and place less demand on "humanness" perception; thus, participants' evaluations of scientific materials may be less susceptible to the influence of an AI label.

Several limitations of the present research warrant attention. First, this study primarily underscores a "label effect." It is noteworthy that all experimental materials, including those attributed to the "human-created" condition, were AI-generated. Consequently, the observed evaluative differences in this study cannot be directly generalized to real-world comparisons between genuinely AI-originated and human-originated works. Meanwhile, in the present study, the specific painting stimuli varied across trials, and the painting-creator label pairings were determined using a pseudo-randomized matching procedure. This approach may have inadvertently allowed the unique content of particular paintings to exert a greater influence on participants' aesthetic evaluation processes, potentially overshadowing the effect of the label itself. Future research investigating label effects of this nature could benefit from employing a fully randomized stimulus-label matching paradigm, or designs with even higher ecological validity, to more effectively explore individuals' attitudes toward AI-labeled products. Additionally, there is potential for such biases to generalize to individuals who use AI, leading to social stigmatization (Dang & Liu, 2024; Reif et al., 2025). To address these gaps, future research could employ diverse experimental paradigms to more comprehensively capture the dynamics of human–AI interaction. Furthermore, based on a convenience sampling approach, all participants in this study were local university students. This limitation in sample diversity may constrain the generalizability of the findings. Consequently, future research should aim to replicate these results using larger and more diverse samples drawn from various countries and age groups to enhance the reliability of the conclusions. Additionally, all participants in this research were university students without professional art training. However, the evaluation of artworks such as paintings may involve a substantial domain-specific expertise gap. Evaluation criteria employed by experts likely significantly differ from those used by non-experts. This implies a promising direction for future research: investigators could compare how art experts versus non-experts evaluate artworks created by humans versus those generated by AI.

AI is becoming an increasingly integral part of human life, leading society towards a "human–machine symbiosis" paradigm. However, from a dialectical standpoint, the widespread use of AI may encroach upon the social space traditionally occupied by humans in the realm like artistic creativity. And the over-reliance on AI may diminish human autonomy and agency (Krakowski, 2025). Therefore, the lower evaluations observed for AI-labeled paintings in this study may reflect a form of bias. Alternatively, they could represent a rational response, an expression of humans safeguarding their perceived primacy and agency within domains closely tied to artistic expression. Whether AI should truly be allowed to assume the role of a primary creator in the field of artistic creativity remains an open question that requires further practical exploration and experimentation. However, until a definitive answer to this question is reached, maintaining an evaluative bias against AI-labeled paintings may not necessarily be a negative phenomenon.

Taking AI-labeled painting reproduction as a case, the present research identified the existence of human bias against AI-labeled works and examined potential influencing factors, including priming attitudes, perceived effort, sense of threat, emotional focus, and task type. These findings extended the traditional theory of algorithm aversion to the context of generative AI. Moreover, the research provides valuable insights for fostering greater objective perception of AI and improving human–AI interactions, while also offering guidance for optimizing the design of future AI systems.

CRediT authorship contribution statement

Wenyu Zhang: Writing – review & editing, Writing – original draft, Visualization, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Ling Huang:** Formal analysis, Data curation, Conceptualization. **Jiaxin Ding:** Writing – original draft, Data curation. **Cong Xie:** Writing – original draft, Visualization. **Jiaxin Mu:** Data curation, Conceptualization. **Ning Hao:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Conceptualization.

Declaration of the use of AI

The paintings used in this research were genrerated using AI tools (GPT-4, Artbreeder). During the preparation of this work the author used Deepseek V3 in order to polish the language. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

Funding

This work was sponsored by the Humanity and Social Science Foundation of Ministry of Education of China (24YJA190004) to NH.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank all participants who took part in this study.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2026.101023.

Data availability

All the research materials and data can be obtained on the OSF website: https://osf.io/j528w/?view_only=4e4d346b666c4b3ca84048046609331b.

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