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Investigating the negative bias towards artificial intelligence: Effects of prior assignment of AI-authorship on the aesthetic appreciation of abstract paintings

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A R T I C L E I N F O

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Art, regarded as one of the last bulwarks of human prerogatives, is a valid model for investigating the relationship between humans and Artificial Intelligence (AI). Recent studies investigated the response to human-made vs. AI-made artworks, reporting evidence of either a negative bias towards the latter or no difference. Here, we investigated whether prior knowledge of authorship can influence the aesthetic appreciation of two abstract paintings by manipulating the pre-assignment of human- vs. AI-authorship. In the ecological setting of an art fair, participants were asked to explicitly rate their aesthetic appreciation, while psychophysiological measure - electrodermal activity (EDA) and heart rate (HR) - were recorded during the observation of the two paintings. Presentation order was balanced among participants and artworks. Results show that when the human-declared painting was shown as first, aesthetic judgement on the AI-declared painting were lower, while with the opposite presentation order judgements were equal. Furthermore, although no modulation of HR was found, EDA activation was always higher during the second presentation. In line with literature, the results showed that looking at abstract artworks reduces the negative bias towards AI. However, the negative bias still emerges when AI-artworks are implicitly compared to human-artworks. Implications are discussed.

1. Introduction

How people judge and deal with Artificial Intelligence (AI) products has become a hot issue in recent years (Peeters et al., 2021; Pelau et al., 2021; Shneiderman, 2021). Although the human-AI relationship and interaction is embraced with good perspective in some areas (Tomašev et al., 2020), recent studies suggest that people show both explicit and implicit bias towards AI (Fietta et al., 2021; Liang & Lee, 2017; Rzepka & Berger, 2018; Sartori & Bocca, 2022). A deeper understanding of the nature and the dynamics of this negative bias is an urgent need in a

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world that increasingly delegates to AI assessments and decisions encompassing the most diverse fields of our society, such as economics, politics, health, and culture (Bickley et al., 2022; Giordano et al., 2021; Poel et al., 2018; Ransbotham et al., 2021).

The negative bias towards AI appears particularly pronounced when artificial intelligence is employed in contexts that are typically considered as belonging to humans, i.e., when abilities such as abstraction, emotional expression or creativity are attributed to artificial agents (Boden, 1998; Ding, 2022; Gaut, 2010; Hong, 2018; Kurzweil, 2005; Wilson, 2011). Concerning the latter, in the last decade, the growing implementation of artificial neural networks (Graupe, 2013), machine learning (Mahesh, 2020), and generative adversarial networks (Aggarwal et al., 2021) has posed a real challenge to the concept of artistic creativity (Anantrasirichai & Bull, 2021; Elgammal et al., 2017). Up until now, artistic creativity has been intended exclusively as a human product and typically assumed to be a quintessential characteristic of human beings (Arielli & Manovich, 2022; Baas et al., 2015; Sawyer, 2011; Sternberg, 1999). However, we are now facing a new era in which AI shows creative abilities *per se* (Mazzone & Elgammal, 2019, March; Miller, 2019; Pereira, 2007), a longstanding idea that already existed in the founders of computing science (Lovelace, 1843; Turing, 1950).

Nowadays, AI can "write" sonnets inspired by Shakespeare's style (Amabile, 2020) or full-length poems and texts starting from few inputs (e.g., see Liang et al., 2021; Numero Cromatico, 2021, 2022), "compose" music (Dannenberg, 2006; Gioti, 2021; Miranda, 1995) or "paint" both representational and abstract visual artworks (Boden, 1998; Colton, 2012; Elgammal et al., 2017; Marzano & Novembre, 2017; Yu, 2016). The current ability of computational creativity is substantiated by the fact that AI-made artworks have been acknowledged as rank artworks by the art-system, exhibited in important museums, and sold by international auction houses for thousands of dollars (Goenaga, 2020).

Although the field of computational modelling of human creativity (Boden, 1996, 1998; Gobet & Sala, 2019) and its usage (e.g., Eshraghian, 2020; Ihalainen, 2018) are becoming increasingly influential issues, how people deal with visual artworks made by AI has not been systematically investigated yet (Arriagada, 2020).

The relationship between Humans and AI in the art context was initially studied in 2006 mainly using two types of approach: some scholars wondered whether people could discriminate between human-made and AI-made artworks (a sort of Turing Test; see French, 2000), while others investigated whether aesthetic appreciation was biased towards Human or AI authorship. These two approaches reflect the two main issues when facing the Human-AI relationship: 1) can we distinguish what is Human-made from what is AI-made? and 2) are we biased when judging a product of AI?

Most studies reported that both visual artworks and musical compositions can be recognized, to some extent, by humans, especially by experts of a specific art field (Chamberlain et al., 2018; Hong & Curran, 2019; Moffat & Kelly, 2006; but see Gangadharbatla, 2022), and that AI-made or computer-made artworks are systematically considered less pleasant than human-made ones (Chamberlain et al., 2018; Kirk et al., 2009; Moffat & Kelly, 2006; Ragot et al., 2020). However, other studies did not confirm the existence of this negative bias (Gangadharbatla, 2022; Hong & Curran, 2019; Israfilzade, 2020; Xu & Hsu, 2020) leaving the issue unresolved.

Only a few among these studies explicitly declared authorship before exposure to the paintings; none of them recorded implicit psychophysiological measures to be associated with the self-reported aesthetic judgments by participants. Furthermore, none of these studies carried out prior analysis of the bottom-up properties of the artworks used in the study being an element which can notch the results. Another important aspect to consider when studying aesthetic experience is that art is typically experienced in an ecological environment, namely art exhibitions, museums, theatres or art fairs, and as it has been recently discussed, the evaluation of aesthetic experience in the laboratory setting or, as an alternative, the use of online surveys has a poor ecological value and can *per se* lower the intensity of art fruition (Brieber et al., 2015; Carbon, 2019, 2020). The development of new *easy-to-use* portable and reliable tools for electrophysiological recording in ecological settings is contributing to paving the way to new methodological frameworks for studying the different levels of artistic enjoyment also outside the laboratory.

Based on these premises, in this study we investigated whether aesthetic appreciation of abstract artworks presented in an ecological setting can be influenced by prior knowledge of authorship when one of the authors is declared as human or non-human (AI). To this aim, we manipulated prior knowledge of authorship on two unknown abstract paintings by declaring them as made by a "Human" or by an "AI", even if they were both human-made. We collected participants' explicit aesthetic appreciation scores *after* observation of each painting, and autonomic psychophysiological measures *during* painting observation, i.e., electrodermal activity (EDA) and heart rate (HR), taken as measures of arousal and emotional valence respectively (Legrand et al., 2021; Russell & Barrett, 1999).

Importantly, we focused on a factor that was neglected in previous studies, i.e., the role of order presentation, that is, the effect on aesthetic appreciation of the first authorship-assignment on the following one. We did this in a two-phase presentation paradigm based on a previous experimental design by Kruger et al. (2004), that allowed us to investigate the order-effect between the two authorship-assignments. Ultimately, since some studies have reported that art-expertise and age can have a role respectively on aesthetic appreciation (Silvia & Berg, 2011; Yeh & Peng, 2018) and on AI judgement (Cameron & Maguire, 2017), we also took these variables into consideration.

Based on previous findings, we were expecting a negative bias towards the AI-associated artworks. However, we hypothesized an attenuation of this bias given the use of abstract paintings, which are more associated with AI and less associated with the author's subjective or emotional contents (Chamberlain et al., 2018; Gangadharbatla, 2022). Nevertheless, we hypothesized that the presentation order of the two artworks could have affected participants' responses by acting as a trigger of implicit comparison mechanisms between what we declared as Human-made vs. AI-made (Moore, 1999). To explore this latter hypothesis, we measured participants' EDA and HR as implicit measures of psychophysiological activation (e.g., Modica et al., 2018; Starcke et al., 2009). Indeed, given that the selected abstract paintings were chosen for their intention to create a neutral emotional state, we hypothesized variation in EDA or HR to occur as a result of the authorship assignment or the presentation order.

The scope of this study has various implications, that span from the study of aesthetic experience to the psychology of Human-AI relationship; thus, it is addressed to a multidisciplinary audience of scholars in neuroaesthetics, psychology, and human-computer interaction.

2. Review of the literature: human-made vs. AI-made artworks

The majority of the studies contrasting human vs. computer- or AI-made artworks have reported the existence of a negative bias towards the latter. The field of music was one of the first to be investigated in respect to appreciation of human- vs. computer-made compositions. By using musical compositions made by humans and computers, Moffat and Kelly (2006) found that, not only participants were able to discriminate between the two types of compositions, but also that there was a preference towards human-generated musical pieces. Interestingly, in this study there was no effect when the authors interchanged the labels "human"- and "computer"-generated musical pieces, demonstrating that the clear preference towards human-made musical pieces was the effect of a cognitive bias, which was greater in musicians (Moffat & Kelly, 2006). In Kirk et al. (2009), participants were exposed to images declared as derived from an Art gallery or generated through a computer using Photoshop. Results showed that the images that were labelled as computer-generated were valued as less pleasing even though they were identical to those declared as belonging to an art gallery. Chamberlain et al. (2018) compared human-with computer-made visual artworks. The authors investigated both the ability to discriminate between computer- and human-made artworks (i.e., categorization task), and their aesthetic appreciation. Results showed, again, a negative bias towards computer-generated artworks in aesthetic appreciation, which was reduced when participants saw a robotic artist in action. Furthermore, in the categorization task, the authors observed that participants categorized the representational artworks more as human-made than computer-made (Chamberlain et al., 2018). Ultimately, Ragot et al. (2020) used a priming paradigm in which information about the authorship was both priming-induced and real through direct assignment. They showed that AI-artworks were less appreciated than human-artworks and that they were perceived as less beautiful, novel, and meaningful than paintings presented as made by a human (Ragot et al., 2020).

Although there is a pool of references reporting a negative bias towards AI-made artworks, results from other studies do not support these findings. Hong and Curran (2019), for instance, conducted an online survey experiment, in which they investigated whether AI-created artworks and human-created artworks were judged as equivalent in their artistic value, taking in consideration eight dimensions, i.e., originality, the degree of improvement, composition, development of personal style, experimentation, expression, successful communication of idea, and aesthetic value, and whether the artworks attributed to an AI-identity received a lower rating compared to artworks that were attributed to a human identity. They found that participants were able to distinguish between Human- and AI-made artworks, however they did not find differences in the artistic value ratings after the assignments of human and AI-authorship, i.e., the acknowledgment of the identity of the artist, either AI or human, did not influence the evaluation of artworks in none of the five dimensions taken into consideration. Israfilzade (2020) contrasted Human and AI-authorship by presenting the name of the author in the titles of two abstract paintings, hence authorship manipulation was not given *a-priori* but during the presentation. The authors, considering Berlyne's theory (Berlyne, 1971, 1974), evaluated a behavioral measure of arousal derived from collative factors and found that participants rated abstract paintings as more novel and surprising when AI accompanied the title, while no effect was found for complexity, interestingness, and ambiguity – the other collative factors analysed (Israfilzade, 2020).

Xu and Hsu (2020, September) investigated whether AI-made artworks can elicit emotions as human-made artworks. They studied the emotions the observers felt when looking at the abstract paintings made by humans and AI, evaluating participants' emotional response with a self-report instrument, the Geneva Emotional Wheel (GEW; Scherer, 2005; Scherer et al., 2013). Results showed that, although participants tended to respond to AI-made paintings with high scores in three positive emotions, i.e., joy, pleasure, and love, the human-made paintings were generally better at eliciting people's aesthetic experience and in arousing more abundant and intense emotional responses.

In a survey experiment, Gangadharbatla (2022) investigated whether participants were able to identify artworks created by AI and whether the attribution knowledge and the type of artwork (abstract vs. representational) had a role in the artwork's perception. The author found that participants were not able to identify the artworks, showing that only one artwork was correctly identified, i.e., the abstract painting made by AI - a finding that resembles the one reported by Chamberlain et al. (2018). However, like Hong and Curran (2019), it was not found an overall bias towards AI when authorship was manipulated. Interestingly, also in this study it was found that participants' evaluation interacted with the type of painting: the abstract artworks were judged as more appreciated when they were associated with AI, while the representational paintings were less appreciated when associated with AI even when they were AI-made.

Overall, the studies that tackle the issue of humans' responses to AI's ability to create artworks are methodologically inhomogeneous and reported controversial results. More studies with higher consistency in methodology are needed and no studies have been conducted in an ecological environment yet, which is central for art fruition.

2.1. The value of a multidisciplinary approach to the study of aesthetic experience

The integration of knowledge from different disciplinary areas, such as neuroscience, psychology, and human-computer interaction in the study of aesthetic experience is central for developing new tools for the implementation of communicative strategies aimed at a better and sustainable relationship between humans and AI. Being art one of the most evolved and complex amongst human activities - just as science is - and difficult to be implemented by an artificial agent, it represents a great model for studying Human-AI interaction (Mazzone & Elgammal, 2019).

As for many other fields, in the last decades, neuroscientific disciplines have contributed also to the investigation of aesthetic experience. The relationship between art and neuroscience has led to a new conception of both beauty and aesthetic appreciation, which validated the idea that these are not absolute values but rather that they change among individuals, populations, and cultures (e.g., Chatterjee, 2010;Che et al., 2018; Jacobsen, 2006; Chatterjee & Vartanian, 2016; Nadal & Chatterjee, 2019; Pearce et al., 2016). According to this view, aesthetic experience in the visual domain is not a simple response to the physical properties or configurations of an artwork, but rather a subjective experience actively built by the beholder (Corradi et al., 2020; Nadal et al., 2017; Gallese & Di Dio, 2012). Indeed, aesthetic experience is a multifaceted process consisting of different levels of processing at the perceptive, emotional, cognitive, and neural domains, arising from the objective and subjective factors related to the artwork (Leder et al., 2004; Leder & Nadal, 2014). Hence, in addition to low-level factors, such as colors and shapes, several studies have shown that aesthetic appreciation and judgement can be modulated on the basis of high-level factors, such as expectations and predictions (Egermann et al., 2013; Salimpoor et al., 2011), beliefs (Huang et al., 2011; Kirk et al., 2009; Locher, 2015), prior experience (Pang et al., 2013), available information (Lengger et al., 2007; Swami, 2013), and context (Brieber et al., 2014, 2015; Pelowski et al., 2017). It follows that even non-sensory prior information might influence the viewer's experience, an issue already acknowledged in the context of art history (e.g., Goodman, 1976).

Here we focused on the influence of authorship on aesthetic appreciation of visual artworks, by manipulating the information about "who made" the artwork before exposing it to the observers. The role of authorship has always been a central argument among art scholars. However, only a few experimental studies reported evidence on how *a priori* knowledge of authorship can influence aesthetic appreciation. A study by Huang et al. (2011) demonstrated how declarations of authenticity of Rembrandt's painting, divided into "Authentic" and "Copy", induces differential brain regions activation in the observers, which can be correlated both to a more suspicious attitude in front of the declaration of "Copy" and a more pleasant reaction in response to what is declared as "Authentic". For instance, visual cortical areas sensitive to face and object recognition were not differentially activated by the manipulation of authenticity, whereas the frontopolar cortex, right middle temporal gyrus, right precuneus, and orbito-frontal cortex were activated differently in response to picture of paintings declared as "Authentic" or "Copy" (Huang et al., 2011). These brain areas have been associated with several higher cognitive functions, including consciousness, memory, and the experience of agency (Cavanna & Trimble, 2006; Koechlin & Hyafil, 2007), validating the idea that aesthetic experience under this condition was not purely dependent on the sensorial components of the artwork.

The above-mentioned approach has the high value of directly correlating neural activity with participant's task, yet it has the disadvantage that it needs the employment of expensive techniques to be used necessarily in a controlled laboratory environment, which has been shown to lower the artistic status of the exhibited objects (Brieber et al., 2015) and the intensity of the experience (Carbon, 2019, 2020).

Besides low-level factors of visual perception or high-level factors of cognitive judgement in aesthetic experience, emotions have a pivotal role (Chatterjee & Vartanian, 2016; Leder et al., 2004; Leder & Nadal, 2014), to the point that many scholars have started to talk and discuss about "aesthetic emotions" as a specific category of emotions (Menninghaus et al., 2019; Skov & Nadal, 2020). A common factor of emotional activation is increased arousal due to activation of the sympathetic nervous system (Kreibig, 2010; Levenson, 2014). Recently, measures of electrophysiological activation have been effectively employed as markers for assessing emotional states in humans (Fingerhut & Prinz, 2020; Silvia, 2005; Skov & Nadal, 2020).

Based on this assumption, measurements of electrodermal activity (EDA) and heart rate (HR) have been employed as indexes of arousal level in studies evaluating advertising perception (Cartocci et al., 2017; Lajante et al., 2020; Modica et al., 2018), music (Schaefer, 2017; Xu et al., 2021), and artworks appreciation (Babiloni et al., 2014; Cartocci et al., 2021; Fekete et al., 2022). For instance, it has recently been shown that increased arousal, as measured by EDA, goes hand in hand with aesthetic judgement and appreciation (Cartocci et al., 2021). Interestingly, according to the theory by Russell and Barret of the circumplex model of affect (Russell & Barrett, 1999), arousal is better indexed by skin conductance measures, while emotional valence by heart rate evaluation. Recently, this distinction has been used to study the modulation of heart rate by stimuli valence in the field of memory research (Legrand et al., 2021). Thus, having measures of both EDA and HR can work as a valid tool for obtaining evaluations of the implicit non-cognitive mechanisms that participants engage during a task. Since these indices are reliably recordable inside and outside the laboratory setting, they appear to suit well for correlating the explicit and implicit responses recorded by participants in an experiment such as the one we conducted. Indeed, our focus was the evaluation in an ecological context of works of art with different declared authorship, which can easily be affected by cognitive factors such as the prejudice against AI. Thus, we reasoned that in our design a monitoring of the emotional engagement of participants could have helped in the interpretation of participants' explicit responses (Menninghaus et al., 2019; Skov & Nadal, 2020; Wassiliwizky & Menninghaus, 2021).

3. Materials and methods

3.1. Participants

One hundred and ten participants took part in this study (66 females; mean age = 37.34 years, SD = 13.53; range 20–70 years-old). The number of participants was pre-planned according to an *a priori* sample estimation made using the software G*Power 3 (Faul, Erdfelder, Buchner, & Lang, 2009), with the assumptions of medium effect sizes ($\eta_p^2 = 0.08$) and statistical power ($\beta = 0.90$). The statistical tool established that the minimum sample size required was 46 participants *per* group. To ensure an adequate number of participants, we enrolled 55 participants *per* group. All participants were recruited as volunteers during "*ArtVerona Fiera dell'Arte*", a contemporary art fair which takes place in the city of Verona (Italy). Each participant reported whether he/she was an art expert (i.e., artist, art scholar, art collector, designer; N = 67; 42 females) or non-expert (i.e., general audience; N = 43; 24 females).

All participants had normal or corrected-to-normal vision and reported not being color-blind. Informed consent was obtained from all participants prior to the start of the experimental session.

3.2. Apparatus and stimuli

The stimuli were two paintings selected from the series "Verbo-visual tests" (Gagliardi, 2015; Numero Cromatico collection) (see Fig. 1). The selection criterion of the two paintings was based on the following three assumptions and purposes: (a) to use abstract paintings, with the aim of evaluating whether the negative bias towards AI is attenuated by the use of non-representational artworks (Chamberlain et al., 2018; Gangadharbatla, 2022); (b) to use abstract paintings that have never been shown to the public before, with the aim of avoiding that any participant could recognize or be familiar with the paintings; (c) to use abstract paintings that, although different, were formally and qualitatively similar, with the aim of excluding bias due to the formal features of the paintings on explicit aesthetic appreciation and psychophysiological parameters (Pasquier et al., 2016). Thus, the selected paintings were both abstract, made by the same artist using the same method, with the main difference being the color used for some of the painted shapes (yellow or red) (see Fig. 1). Given that color is an element that can contribute to visual saliency (e.g., Tajima & Komine, 2015; Zhang et al., 2016), and considering that its contribution to bottom-up processing can be measured (Itti et al., 1998), we first checked that the different color used in each painting did not influence bottom-up perception in terms of salience. We first generated two saliency maps of the paintings by using the graph-based visual saliency (GBVS) algorithm (Harel et al., 2007). To compare the saliency maps and to exclude other features that could have contributed to saliency, each final saliency map has been scaled on the saliency map of the black and white corresponding painting, obtaining two color-only saliency maps. The color-only saliency scores obtained from each painting were statistically compared through a sample *t*-test that showed no significant differences between the two paintings in terms of saliency ($t_{(109)} = 1.7, p = .1$).

For each participant two electrophysiological measures were recorded during observation of the paintings: the electrodermal activity (EDA) and heart rate (HR), by means of a Shimmer EDA+ (Shimmer sensing) system with a sampling rate of 64 Hz. The EDA was acquired through the constant voltage method (0.5 V). Electrodes were attached on the participants' non-dominant hand, to the palmar side of the middle phalanges of the second and third fingers (Boucsein, 2012). The tonic component of the skin conductance level was obtained using "LEDAlab software" (Benedek & Kaernbach, 2010). The HR has been obtained from the Blood Volume Pulse (BVP) signals by using the Pan-Tompkins algorithm (Pan & Tompkins, 1985). Finally, the EDA tonic component and the HR have been standardized on the mean and standard deviation scores obtained during the baseline conditions.

3.3. Procedure

Participants were engaged in an aesthetic judgement task, in which they were asked to judge two abstract paintings presented in a randomized order (see Kruger et al., 2004). The paintings were presented at 2 m from participants in an ecological environment (i.e., an art fair), in a comfortable place where each participant was alone with the experimenter. Although both paintings were made by a human painter, we manipulated the authorship assignment by pre-assigning "Human" or "AI" before each painting's presentation. The EDA and HR were recorded during the whole task. Each participant was involved in a "one-shot experimental trial" consisting of the following subsequent phases (Fig. 2): (1) first baseline activity recording (1 min); (2) exposition to the first white covered painting; (3) author-assignment to the first painting; (4) first painting presentation (1 min); (5) aesthetic evaluation judgement; (6) exposition to the second white covered painting; (7) author-assignment to the second painting; (8) second painting presentation (1 min); (9) aesthetic evaluation judgement; (10) second baseline activity recording (1 min). At the beginning of the procedure participants were positioned in front of the first painting covered by a white cloth, which they were asked to look at for 1 min. They were then informed that they would see a painting made by a human being (Human) or by an Artificial Intelligence (AI). After this information the first painting was uncovered, and participants were asked to observe it

Fig. 1. Photographs of the artworks used in the experiment. Left, Abstract 12, Acrylic on canvas, 120 × 120 cm; Right: Abstract 18, Acrylic on canvas, 120 × 120 cm.

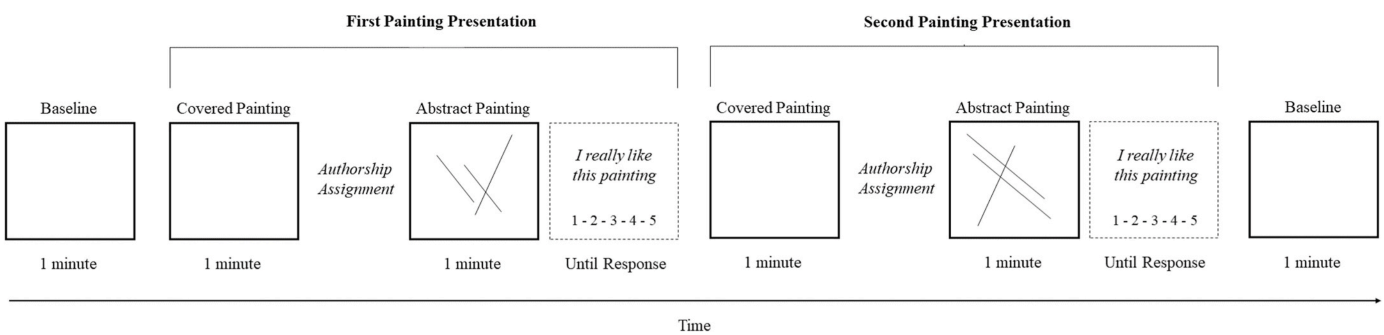

Fig. 2. Schematic representation of the experimental procedure. Each trial started with a 1-min baseline activity recording of the electrophysiological measures (EDA and HR) and the presentation of a covered painting. Then, the experimenter declared to the participants the authorship assignment of the painting, and the first painting was presented for 1 min. Subsequently, participants were asked to judge the painting on a 5-point Likert scale. The same sequence was presented for the second painting. 1 min baseline activity was recorded at the end of the sequence.

for 1 min. Subsequently, participants were asked to say how much they agreed with the statement "I really like this painting", selecting the response on a 5-point Likert scale from 1 (totally disagree) to 5 (totally agree) (Kim et al., 1998), with no time limitation. Then, participants were asked to look at the second painting by following the same procedure. The presentation order as well as the authorship assigned to each painting was counterbalanced among participants.

3.4. *Experimental design and data analysis*

All the analyses were conducted by means of mixed ANOVA followed by *post-hoc* pairwise *t*-tests corrected by Bonferroni's method for multiple comparisons. We report η_p^2 for ANOVA and Cohen's d for *t*-tests as measures of effect size. In order to investigate the presentation-order effect, first, we divided participants into two groups based on presentation order: Group A (N = 55) saw the Human-painting as first and the AI-painting as second, Group B (N = 55) the opposite. We ran a 2 × 2 mixed ANOVA with Assignment (2 levels: Human vs. AI) as within-subjects variable and Group (2 levels: Group A vs. Group B) as between-subjects variable, and mean score in aesthetic judgement, EDA, and HR as dependent variables. The absolute aesthetic appreciation scores, EDA and HR values for each painting were compared with a paired sample *t*-test. Prior to the main analyses we checked whether aesthetic appreciation and the psychophysiological scores were equal for both paintings. Results showed that both aesthetic appreciation scores ($t_{(109)} = -1.73, p = .090, d = -0.16$), HR ($t_{(109)} = -1.00, p = .32, d = -0.09$) and EDA values ($t_{(109)} = -1.387, p = .16, d = -0.13$) were not different between the two paintings, indicating that they were comparable in both explicit and implicit measures.

Furthermore, in order to investigate the role of art expertise, we divided participants into two groups: Art-Expert (N = 67) and Non-Art-Expert (N = 43), and ran three separated 2 × 2 mixed ANOVA with Assignment (2 levels: Human vs. AI) as within-subjects variable and Art Expertise (2 level: Art expert vs. Non-expert) as between-subjects variable, with (a) mean score in aesthetic judgement, (b) EDA and (c) HR as dependent variables.

Ultimately, we also controlled for a possible effect of age. First, we divided participants into two groups (Young vs. Adult), considering the mean age of the group (M: 37.34 years old) as a cut-off between Young (N = 46) and Adult (N = 52) participants. Twelve participants were excluded from this analysis because they did not report their age. Furthermore, we ran a second, more strict analysis, in which we divided participants into Younger vs. Older, considering only individuals whose age was greater or smaller than the mean age (M = 37.34) ± 1 standard deviation (SD = 13.53): Younger (N = 22) were participants with an age lower than 23.80, while Older (N = 29) were all participants who had an age above 50.88. Fifty-nine participants in total were excluded from this latest analysis. For both cases, the same three ANOVAs were run for the presentation-order and art-expertise factors were applied.

4. Results

4.1. *The role of presentation order*

One of the most underestimated effects in previous literature on aesthetic response to Human vs. AI authorship is the presentation order of the stimuli. To take this factor into consideration we balanced the presentation order of the artworks declared as AI-made and Human-made among participants and between the artworks themselves.

4.1.1. Behavioral measures

To investigate the effects of Human- and AI-authorship assignment, we ran a 2 × 2 mixed ANOVA on aesthetic appreciation scores, obtained through the answers to the question "How much do you agree with the sentence: *I really like this painting*". Results showed that both the main effect of Assignment ($F_{(1,108)} = 0.27$, $p = .60$, $\eta^2_p = 0.003$) and Group ($F_{(1,108)} = 2.47$, $p = .12$, $\eta^2_p = 0.022$) were not significant. Instead, the interaction Assignment x Group reached the significance ($F_{(1,108)} = 5.98$, $p = .016$, $\eta^2_p = 0.053$). Pairwise *post-hoc* comparisons revealed that there was a difference between Human and AI assignment in Group A ($t_{(54)} = -2.10$, $p = .038$, d = 0.30), which saw Human as first; whereas, there was no difference between Human and AI assignment in Group B ($t_{(54)} = 1.36$, $p = .18$, d = 0.18) that saw AI as first (Fig. 3). Moreover the *post-hoc* analysis for the factor order showed that AI was significantly different between groups ($t_{(109)} = -2.65$, $p = .014$, d = 0.48) with lower scores when AI was presented as the second painting compared with when it was presented as first. On the contrary, there was no difference for Human between groups ($t_{(109)} = 2.22$, $p = 1.0$, d = 0.001).

4.1.2. Electrophysiological measures

Analysis of EDA scores revealed that both the main effect of Assignment ($F_{(1,108)} = 0.19$, $p = .66$, $\eta^2_p = 0.002$) and Group ($F_{(1,108)} = 0.54$, $p = .46$, $\eta^2_p = 0.005$) were not significant. However, the interaction Assignment x Group reached a statistical difference ($F_{(1,108)} = 97.72$, $p < .001$, $\eta^2_p = 0.47$). Pairwise *post-hoc* comparisons revealed that there was a difference between Human and AI both in Group A ($t_{(55)} = 7.30$, $p < .001$, $d = 1.31$) and Group B ($t_{(54)} = -6.68$, $p < .001$, $d = 1.19$). Specifically, the analyses revealed that EDA activity was higher during the second presentation compared to the first one in both groups (Fig. 4).

Analysis on HR (Fig. 5) scores revealed no main effects of Assignment ($F_{(1,108)} = 0.25$, $p = .62$, $\eta^2_p = 0.002$), Group ($F_{(1,108)} = 0.57$, $p = .57$, $\eta^2_p = 0.003$), nor interaction Assignment x Group ($F_{(1,108)} = 1.76$, $p = .19$, $\eta^2_p = 0.016$).

4.2. The role of art expertise

To investigate the role of art expertise we ran a 2 × 2 mixed ANOVA on aesthetic appreciation scores with Assignment (Human vs. AI) as within-subject factor and Art expertise (art expert vs. non-expert) as between-subjects factor. Results showed that both the main effect of Assignment ($F_{(1,108)} = 0.27$, $p = .60$, $\eta^2_p = 0.003$) and Art expertise ($F_{(1,108)} = 2.44$, $p = .12$, $\eta^2_p = 0.022$) were not significant. The interaction Assignment x Art expertise did not reach significance ($F_{(1,108)} = 0.03$, $p = .91$, $\eta^2_p = 0.053$).

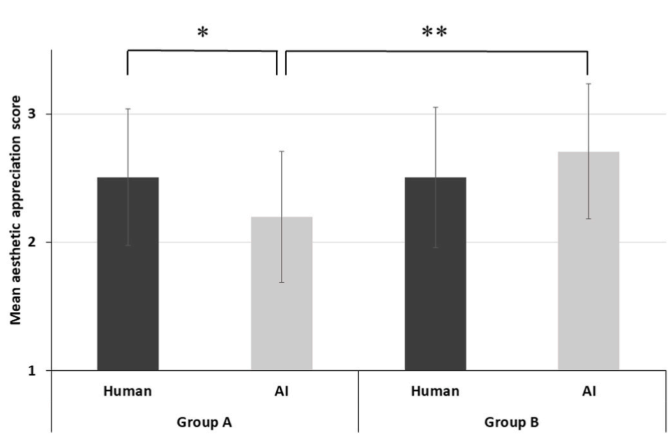

Fig. 3. The influence of prior assignment of authorship on aesthetic appreciation. Bar charts represent the mean ± SD of aesthetic appreciation scores on a 5-point Likert scale for paintings declared as Human- and AI-made for Group A, which saw Human as first, and Group B, which saw AI as first. *p < .01, **p < .001 obtained with Bonferroni correction for post-hoc pairwise comparisons.

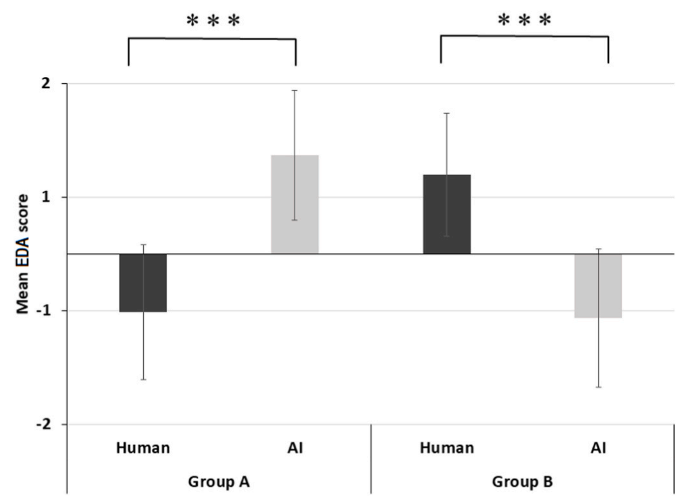

Fig. 4. The influence of prior assignment of authorship on EDA. Bar charts represent the mean ± SD of EDA values for group A and B. ***p < .0001 obtained with Bonferroni correction for post-hoc pairwise comparisons.

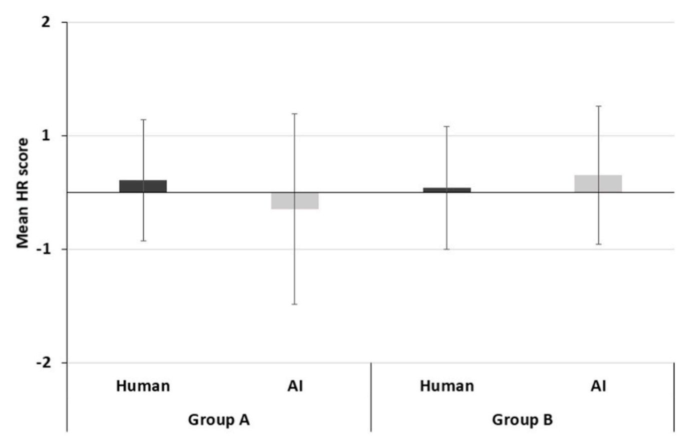

Fig. 5. The influence of prior assignment of authorship on HR. Bar charts represent the mean ± SD of HR values for group A and B.

The same ANOVA was run first on EDA scores, revealing no effect of Assignment ($F_{(1,108)} = 0.27$, $p = .60$, $\eta^2_p = 0.003$) and Art expertise ($F_{(1,108)} = 0.005$, $p = .94$, $\eta^2_p = 0.004$), nor interaction Assignment x Art expertise ($F_{(1,108)} = 0.01$, $p = .91$, $\eta^2_p = 0.001$); analysis of HR scores revealed again no effect of Assignment ($F_{(1,108)} = 0.27$, $p = .60$, $\eta^2_p = 0.003$) and Art expertise ($F_{(1,108)} = 0.44$, $p = .51$, $\eta^2_p = 0.004$), nor interaction Assignment x Art expertise ($F_{(1,108)} = 0.03$, $p = .88$, $\eta^2_p = 0.002$).

4.3. The role of age

To investigate the role of age we ran a 2 × 2 mixed ANOVA on aesthetic appreciation scores with Assignment (Human vs. AI) as within subject factor and Age (young vs. adult) as between factors. Results showed that both the main effect of Assignment ($F_{(1,96)} = 0.76$, $p = .98$, $\eta^2_p = 0.006$) and Age ($F_{(1,96)} = 0.36$, $p = .55$, $\eta^2_p = 0.004$) were not significant, as well as the interaction Assignment x Age ($F_{(1,96)} = 0.12$, $p = .72$, $\eta^2_p = 0.001$). The same ANOVA was first run on EDA scores, revealing no effect of Assignment ($F_{(1,96)} = 0.25$, $p = .62$, $\eta^2_p = 0.003$) and Age ($F_{(1,96)} = 0.58$, $p = .45$, $\eta^2_p = 0.006$), nor interaction Assignment x Age ($F_{(1,96)} = 0.16$, $p = .69$, $\eta^2_p = 0.002$). Similarly, analysis on HR scores revealed no effects of Assignment ($F_{(1,96)} = 0.06$, $p = .94$, $\eta^2_p =$

0.005) and Age ($F_{(1,96)} = 0.32$, $p = .57$, $\eta_p^2 = 0.003$), nor interaction Assignment x Age ($F_{(1,96)} = 3.54$, $p = .07$, $\eta_p^2 = 0.036$). Similar analyses were run on a more stringent distribution of age in which we only considered the youngest and oldest participants (i.e., Younger vs. Older; see Experimental design and data analysis for more details). Also in this case, results showed that there was no effect of Assignment ($F_{(1,49)} = 0.04$, $p = .95$, $\eta_p^2 = 0.005$) and Age ($F_{(1,49)} = 0.57$, $p = .45$, $\eta_p^2 = 0.012$), nor interaction between the two factors ($F_{(1,49)} = 1.59$, $p = .21$, $\eta_p^2 = 0.031$) for aesthetic appreciation, as well as for EDA (Assignment, $F_{(1,49)} = 0.05$, $p = .94$, $\eta_p^2 = 0.005$; Age, $F_{(1,49)} = 0.08$, $p = .77$, $\eta_p^2 = 0.002$; interaction Assignment x Age, $F_{(1,49)} = 1.12$, $p = .29$, $\eta_p^2 = 0.022$) and HR (Assignment, $F_{(1,49)} = 0.03$, $p = .96$, $\eta_p^2 = 0.005$; Age, $F_{(1,49)} = 0.59$, $p = .45$, $\eta_p^2 = 0.012$; interaction Assignment x Age, $F_{(1,49)} = 1.87$, $p = .18$, $\eta_p^2 = 0.037$).

Main results are summarized in Table 1.

5. Discussion

Aesthetic appreciation is an active process influenced by several objective features, external and subjective factors that engage both bottom-up and top-down processes. The degree to which previous knowledge about the author of an artwork impacts on its appreciation is a key issue in art, while it is less studied in psychology research. It is known that, for instance, knowing that an artwork was made by a famous painter or by someone who tries to copy his/her style changes the brain activity engaged in high-level cognitive computations (Huang et al., 2011). In the technological era that we are facing, this issue has also become a matter of AI products, since the recent development of neural networks capable of producing original works of art. To study how people deal with knowing that an artwork is created by an AI, this study investigated the effect of the manipulation of authorship assignment on abstract artworks appreciation by pre-assigning human-made or AI-made authorship to two abstract artworks, both created by a human artist. As an explicit measure of aesthetic appreciation, we asked participants to rate on a 5-point Likert scale the two observed artworks by declaring how much they liked the paintings (Kim et al., 1998; Kruger et al., 2004). During the task we recorded EDA and HR as implicit measures of psychophysiological activation.

In line with previous evidence (Chamberlain et al., 2018; Ragot et al., 2020), our results showed that manipulation of authorship, by contrasting "Human" and "AI" authorship, influences aesthetic appreciation. In accordance with our hypotheses, this modulation did not emerge as an absolute difference between the two authorship-assignments on abstract paintings. Indeed, based on previous studies that compared Human-made and Computer- or AI-made artworks, one could expect an overall difference between Human- vs. AI-assignment (e.g., Moffat & Kelly, 2006; Kirk et al., 2009; Chamberlain et al., 2018; Ragot et al., 2020). Differently, we observed that the difference between the two authorship-assignments emerges as a function of the presentation order (Moore, 1999), i.e., only when participants judge the painting assigned to the human as first, they gave lower scores to that assigned to AI. In parallel, the EDA activity revealed a higher arousal in concomitance with the second presentation irrespective of the experimental manipulation, which suggests a psychophysiological activation plausibly induced by the recruitment of implicit comparison mechanisms, supporting the sensitivity of EDA in detecting unconscious reaction during ambiguous choices and categorization (Starcke et al., 2009). Such autonomic signal-derived reactivity in response to items, possibly objects of biased prejudice, has been also observed when comparing foreign and local products (Modica et al., 2018).

It is important to underline that we did not find a difference on aesthetic appreciation scores when the human-assigned painting was shown after the AI-assigned one. We think that these results further support the idea of a negative bias towards AI-made artworks, considering that participants did not know in advance what they had to do. Hence, in front of two paintings that had similar absolute pleasantness, participants attributed a lower score to the AI-artwork after they already gave a value to the human-artwork; the opposite did not happen because they did not perceive the human-made painting as more pleasant than the AI-made one (i.e., a case of positive bias for human). These results are consistent with the absolute comparable scores collected for the two paintings. Indeed, analysis of the absolute scores of aesthetic appreciations for the two paintings and that of their bottom-up saliency (see in 3.2 Apparatus and stimuli), were both non-different, allowing to exclude that the preference for one of the two paintings or their objective features could have affected the results.

The main factor that could have contributed to the lack of an absolute preference for the painting declared as human-made could be the choice of abstract paintings for our experiment (see Chamberlain et al., 2018; Gangadharbatla, 2022). Chamberlain et al. (2018) reported that, when asked to classify abstract and representational visual artworks as Human- or Computer-made, participants tend to categorize representational artworks as Human-made more than Computer-made. Thus, the abstract paintings we used might have mitigated the negative bias

Table 1
Left side: Behavioral scores (aesthetic appreciations) and electrophysiological scores (EDA and HR) for groups divided for presentation order (upper part), art expertise (middle part), and age (lower part) as function of authorship assignment (Human vs. AI). Standard deviations appear in parentheses. ANOVAs results are reported on the right side of the table. $^*p < .05$, $^{***}p < .001$.

	GROUPS				ANOVA					
	Group A		Group B		Within-subjects variable		Between-subjects variable			
	Painting Presentation		Painting Presentation		Aesthetic appreciation		Presentation order		Interaction	
PRESENTATION ORDER	1° HUMAN	2° AI	1° AI	2° HUMAN	F	p	F	P	F	p
Aesthetic appreciation	2.50 (1.06)	2.20 (1.02)	2.71 (1.10)	2.50 (0.81)	0.27	0.60	2.47	0.12	5.99	0.016*
EDA	−0.51 (1.02)	0.87 (1.09)	−0.57 (0.99)	0.70 (1.13)	0.19	0.66	0.54	0.46	97.71	<.001***
HR	0.10 (1.07)	−0.14 (1.67)	0.15 (0.94)	0.04 (1.31)	0.25	0.61	0.32	0.57	1.76	0.19
	Art-Expert		Non-Expert		Aesthetic appreciation		Art Expertise		Interaction	
EXPERTISE	HUMAN	AI	HUMAN	AI	F	p	F	p	F	p
Aesthetic appreciation	2.40 (0.90)	2.35 (1.06)	2.67 (0.99)	2.60 (1.11)	0.27	0.60	2.44	0.12	0.01	0.90
EDA	0.09 (1.31)	0.16 (1.30)	0.10 (1.13)	0.13 (1.19)	0.08	0.77	0.05	0.94	0.01	0.91
HR	0.11 (1.23)	0.06 (1.40)	0.003 (1.14)	−0.10 (1.31)	0.27	0.60	0.43	0.51	0.03	0.51
	Young		Adult		Aesthetic appreciation		Age		Interaction	
AGE	HUMAN	AI	HUMAN	AI	F	p	F	p	F	p
Aesthetic appreciation	2.52 (1.00)	2.56 (1.10)	2.46 (0.89)	2.42 (1.02)	0.04	0.98	0.36	0.54	0.12	0.72
EDA	0.09 (1.46)	0.36 (1.38)	0.04 (1.09)	0.06 (1.22)	0.25	0.62	0.58	0.45	0.16	0.69
HR	−0.02 (1.15)	0.23 (1.33)	0.12 (1.33)	−0.16 (1.36)	0.06	0.94	0.32	0.57	3.54	0.07

previously reported. Moreover, it has been reported that abstract contents are harder to associate with the subjective feelings of the author, and factors such as anthropomorphism and embodiment have been suggested to be determinant for the expression of a preference towards an artifact (Chamberlain et al., 2018).

Another study in which authors employed abstract paintings was conducted by showing the author's name during the presentation of the stimuli (Israfilzade, 2020) and not before it. In this case, there were no differences between human- and AI-authorship reception on collative factors such as complexity, interestingness, and ambiguity (see Berlyne, 1971, 1974). However, important methodological aspects of this latter study are not clearly reported, such as the way in which the paintings were presented, how long participants could observe them, and the reason for recruiting only one group of young art-students (age range from 17 to 25) - with a strong gender imbalance towards females. These factors could have concealed the emergence of the negative bias towards AI. Moreover, authors used the scoring of collative factors as behavioral measure of the arousal based on Berlyne's model of experimental aesthetics (Berlyne, 1971, 1974), which has caused criticism around the idea of linking collative variable and hedonic value in aesthetic appreciation (Jacobsen, 2006; Silvia, 2005). A study by Xu and Hsu (2020) did not manipulate the assignment of human and AI authorship but evaluated the emotional self-reported response to human- or AI-made abstract paintings, reporting no difference between the authorship assignments. However, the strength of this effect is not clearly described in the study, which involved a small sample (50 participants), and no control for the effects of the painting themselves was reported. A possible reason for the null effect of human vs. AI authorship in this case could be that authors focused on explicit emotional responses to the artworks, which may not be the core of the negative bias towards AI that this and other studies observed. It is possible that, at the base of the emergence of the negative bias, there are more cognitive than emotional factors. In fact, this is also what our data suggest if we look at the null effect on the HR (Fig. 5), considered as a measure of valence (Russell & Barrett, 1999), and the higher value of EDA on the second presentation, considered as a measure of arousal (Russell & Barrett, 1999). In another study, authors found no difference in the scoring of factors such as originality, degree of improvement, composition, development of personal style, experimentation, expression, successful communication of idea, and aesthetic value (Gangadharbatla, 2022). Their results appear in contradiction with ours, however, this study used an unbalanced number of artworks made by AI and Human to administer to participants and, diverging from the explicit evaluation that we asked concerning the pleasantness *personally* felt, the one tested by the author were more objective features of an artwork.

The majority of these studies are survey studies, carried out online. Differently, our study was carried out in an ecological setting, namely an art fair. The art fair and, specifically, an important event such as *Art-Verona*, allowed us to recruit people from diverse ethnic backgrounds. However, ethnicity was not evenly distributed, with most participants being Caucasian.

Together with previous findings, our results suggest the existence of a deeper type of bias, which emerges when people implicitly compare two paintings, or better, when they judge how much they like a painting according to the available information about who made the paintings, i.e., human or AI. The reported lack of effect for HR values and the absence of differences on the appreciation scores for the factors Assignment and Group alone appears in accordance with the interpretation of our results, namely the existence of a cognitive prejudice. This could be explained by the so-called "Beauty-is-Good" stereotype (or "Beauty halo"; Dion et al., 1972), consisting in the mostly unconscious overlap between the explicit beauty judgement and the moral evaluation, known to occur in several domains like mating choices, job hiring (Johnson et al., 2010), politics (Peterson & Palmer, 2017), or even clinical care (Mohamed et al., 2016). In our study, the absolute aesthetic appreciation scores are beauty judgement, while the HR values are the valence evaluation (Mauss & Robinson, 2009), which were both positive and not different based on authorship assignment or order of exposition *per se*. The concordance between the absolute aesthetic scores and the emotional activation revealed by HR values, together with the higher arousal showed in response to the second presentation with the EDA values, support the hypothesis that the recorded negative bias towards AI-made paintings that emerges as an effect of order presentation might be the result of top-down processing.

Other possible factors that can contribute to this negative bias must be considered. A possible interpretation of our results could be related to the reported feeling of fear of AI. It has been documented that the development of AI in the last decades has nourished a general sense of fear about its effect in some aspects of society (Hertzmann, 2018; Li & Huang, 2020). This fear may have different roots: it might come from the idea that AI can steal people's workplaces and put them out of work, or it can be related to the fear of diversity and in-group/out-group theories. In the context of art creation, however, this factor may be less determinant since artists represent a smaller part of the population and are not generally considered as "workers". Moreover, our sample was made of art-enthusiasts and not art-producer, who are the ones from which AI would "steal" the job in this case. Our focus here was on the *ex-novo* creative potential of AI in art production. To this aim, we limited ourselves to declaring that out of the two artworks one was *created* by an AI and one by a human being. A common distinction in AI types is between "weak" and "strong" AI (Al-Rifaie & Bishop, 2015). The former refers to AI capable of performing specific tasks based on specific users' input, while the latter indicates AI that can perform several functions, learn based on inputs and experiences and solve new problems. Thus, while a weak AI can only "grow" thanks to human intervention, a strong AI is theoretically able to do so without it. Albeit it still being a disputed issue, strong AI are those that ultimately will develop human-like consciousness and not only simulate human functions (Ng & Leung, 2020). Our experiment did not delve into these differences. Since we did not ask participants to recognize whether the artworks were AI- or Human-made, nor to attribute them an economic value or compare the two artworks, our approach weakens the chance that participants' response could have been influenced directly by fear or by the feeling of being tricked by the AI. A relevant feeling which could have influenced participants' judgement could have been that of feeling unease with the idea that AI *creates* an artifact, which has always been one of the activities that identifies humans as special beings, like science for instance. However, this is a specific issue that needs further investigation.

Alternatively, the negative bias we observed might be explained by the feeling of lack of intentionality in AI artifacts (e.g., Hawley-Dolan & Winner, 2011) that are typically felt as the result of a computational operation. Concerning art in particular, the prejudice on AI-artworks could be influenced by the conviction that only humans can make art, because AI has no intentionality and no contents to express (Hertzmann, 2018). However, this view of making art for communicating the artist's subjective contents has already been overcome by some strands of contemporary art, which state that an artwork should not express the subjective contents of the artist (e.g., Bill, 1993; Cohen, 1973; LeWitt, 1967; Lombardo, 1991). Considering that our experiment was conducted in a contemporary art fair, most often attended by contemporary art amateurs, collectors, and experts, it is unlikely that our data arise from this kind of prejudice about the art contents. Ultimately, the negative bias towards AI can be the result of an *effort heuristic* effect (Kruger et al., 2004), according to which (art)works that require more time and effort are perceived as more beautiful and valuable than those that require less time and effort. It is possible that, after judging the human painting, participants tended to rate the AI as less appreciated, due to a prejudice according to which human activities are more tiring or time-consuming and valuable than AI ones (see Dutton, 2003, 2009).

5.1. Implications of the study

The results we show have implications in many fields beyond the one of art. Among these, healthcare is one of the most interesting because of the close relationship between the patient, the clinician and the AI taking part in the decision processes on the therapeutic strategy. Many efforts are now being invested to achieve better and personalized diagnoses, treatments, and management of patients across a continuum of care and prevention through the implementation of safe and top-quality digital services that can ensure healthier, independent lives for ageing, sensitive and chronic patients' populations (Triberti, Drosini, & Pravettoni, 2020). This new tendency is addressed at the implementation of remote or in-person AI-based diagnostic and rehabilitation tools for neuropsychophysiological screenings and interventions. In this framework, technicians work for the development of AI and machine learning devices for improving precision in medical strategies. However, for the effectiveness of this new promising approach, patient's psychological response to the "role" of AI, as well as his/her feelings, are important factors to consider. Here we demonstrate that cognitive factors, such as *a priori* knowledge of the author of an artifact can deeply influence people's response. It appears that *a priori* cognitive factors also have the power of influencing a person's response in other fields and even undermine his/her feeling of trust, which is a pivotal variable in healthcare for the patient's positive response to treatments and therapeutic strategies. For instance, Triberti et al. (2020) recently discussed this issue introducing the "third wheel" effect, that may occur and potentially affect the effectiveness of clinical decision-making by delaying or paralyzing AI recommendations when they are difficult to understand or to explain to patients.

Healthcare is only one of the fields interested by the emerging AI-based technologies, which entails several levels of our society, such as politics, education, and cybersecurity (Bickley et al., 2022; Giordano et al., 2021; Poel et al., 2018; Ransbotham et al., 2021). Our data support the need of a more extensive and focused effort towards the divulgation of the positive and safe potential of AI-based programs. Since the active collaborative role of AI-based technologies in human tasks and activities is increasing, a parallel investment to increase the awareness about reliability, potential and role of AI-based intervention and participation in decision-making processes in our societies needs to be afforded by governments and management institutions.

The new field of "eXplainable Artificial Intelligence" (commonly abbreviated as XAI) is specifically aimed at the research of AI's transparency, interpretability, and ability to explain its own elaboration process, with the idea that users will be better equipped to understand, and therefore trust, the intelligent agents (Miller, 2019). The communication process among recipients and tenderers that employ AI products can significantly affect the well-being, quality of life or decisions of the recipients in different ways that are still underexplored in comparison to the speed with which AI is spreading. A feeling of distrust, doubt, disagreement or ambiguity in the healthcare, politics, and social contexts, such as the one of art, should be properly considered in our era and more efforts are needed to take care of these negative feelings.

What can or cannot AI do? To what extent can it entail our activities as humans? In conducting this and our current research, we experienced ambivalent and contrasting feelings among participants: some were astonished and positively surprised, others were scared and even bothered by the fact that the artwork was made by an AI. In the art context, the issue becomes even more complicated if one considers that aesthetics, creativity, and art in general are considered as quintessentially human domains, and abilities that represent the final bulwark against the seemingly unstoppable advances of AI (Manovich & Arielli, 2021, 2022). Yet, we are already close to that point: AI can create new art products, such as music or paintings, that have succeeded in fooling humans with the Turing Test (French, 2000). Experts are harder to be fooled by the Turing test, but it may be a matter of time until AI improves enough to deceive them as well.

One could argue that AI produces artworks that are not properly creative *per se*, but rather mimic existing styles. Yet again, it might be a matter of time until AI-made artworks are judged as aesthetically superior to their human variants and can push our cultural boundaries towards new horizons (Jackson, 2017; Manovich & Arielli, 2021, 2022). Nonetheless, art is possibly the field that will be less affected from a theoretical and economical point of view by AI potentials, as the historical and market value of an artwork is determined by factors that are more complex than the simple reaction of individuals.

Further research on the communication of the new techniques and types of AI available in the field of art production is necessary for improving the spread and profitability of AI-made artworks, as well as knowing more about peoples' responses to AI in general. The public needs to better understand the potential of this new frontier in the art field in order to overcome the negative feeling associated with AI agents. To this aim, we think that it is important to develop and implement specific communication studies, surveys, courses and workshops in fine art institutes, universities – in both humanistic and scientific departments –, museums and schools.

In history, each time a new technological advancement is reached, it needs to be explained to both experts and the general public in order to diffuse a feeling of awareness and knowledge about it. Focused communicative approaches will have the indirect effect of ameliorating the profitability of AI-made artworks in the market. A new positive ecological relationship between humans and AI agents needs to be developed to reach this ambitious goal.

Overall, our data suggest that people are not yet fully prepared to embrace the new incoming era. More studies are needed to investigate the psychosocial effects of AI on the different practices in which it is being implemented, as well as test the efficacy of communication strategies aimed at properly informing target populations, by taking into consideration the several sociodemographic factors that can be involved, such as the age, education, and ethnographic characteristics.

6. Conclusions

We innovatively introduced the use of implicit psychophysiological measures such as EDA and HR, along with self-reported judgement of aesthetic appreciation of two abstract paintings presented in an ecological art-environment. Our results reported first evidence of the effect of implicit comparison within the manipulation of the pre-assignment of authorship between human and AI to unknown abstract artworks. Specifically, we showed that, although the negative bias towards AI is reduced by the use of abstract artworks, it still occurs when the artwork that has been assigned to AI-authorship is compared to the artwork assigned to human-authorship.

The overall conclusion of the present research is that perception is strictly tied to our previous knowledge and to the context. Our data support the view that what we experience when observing an artwork is not just the result of a passive biological activation guided by its formal features, but instead it is an active operation in the observer's brain that can be influenced by the available information. Indeed, we showed that the lower pleasantness attributed to an AI-product is the result of a prejudice, and not a pure, unbiased judgement. In a world that is always more "AI-dependent", it is crucial to understand how people deal with AI, to act in time with proper educational and communicative campaigns that can give people the proper tools and knowledge for coping with the AI progress. In accordance with our results, previous data have demonstrated that the negative bias towards AI-made artifacts can be manipulated and inverted in people that are prepared and somehow "educated" to what they are looking at (Chamberlain et al., 2018). This latter evidence, like the one we showed here, suggests the need for a better communication on the positive potentials of AI and human-AI relationship, also in fields that are thought to be a human prerogative, such as art and creativity.

6.1. Limitation and future directions

The data acquisition of our experiment was conducted in an ecological context, namely an art fair. Thus, the validity of the collected data in ecological context is still controversial, due to the potential influence that distracting or external factors could exert on participants. On the other hand, it has been shown that the aesthetic experience in the art context can enhance the artistic status of the exhibited objects (Brieber et al., 2015) and intensify the art experience (Carbon, 2019, 2020). The number of studies that made this choice in regards to the context in which the research is carried out has increased in the last decades (Mastandrea et al., 2021; Siri et al., 2018; Tröndle et al., 2014), as the paucity and sterility of the laboratory setting may lower the power of the aesthetic experience, thus affecting the observer's response. Moreover, innovative tools for brain activity recording are becoming easier to use outside the laboratory setting, allowing the implementation of research in art perception also in museums and art contexts. Future experiments will have to corroborate the evidence obtained in the present study with the correlation of brain activity and other psychophysiological investigations.

Authors contributions

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Data availability statement

The raw data supporting the conclusions of this manuscript will be made available by the authors upon reasonable request.

Declaration of competing interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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