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Co-creating art with generative artificial intelligence: Implications for artworks and artists

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ABSTRACT

Synthetic visual art is becoming a commodity due to generative artificial intelligence (AI). The trend of using AI for co-creation will not spare artists' creative processes, and it is important to understand how the use of generative AI at different stages of the creative process affects both the evaluation of the artist and the result of the human-machine collaboration (i.e., the visual artifact). In three experiments (N = 560), this research explores how the evaluation of artworks is transformed by the revelation that the artist collaborated with AI at different stages of the creative process. The results show that co-created art is less liked and recognized, especially when AI was used in the implementation stage. While co-created art is perceived as more novel, it lacks creative authenticity, which exerts a dominant influence. The results also show that artists' perceptions suffer from the co-creation process, and that artists who co-create are less admired because they are perceived as less authentic. Two boundary conditions are identified. The negative effect can be mitigated by disclosing the level of artist involvement in co-creation with AI (e.g., by training the algorithm on a curated set of images vs. simply prompting an off-the-shelf AI image generator). In the context of art that is perceived as commercially motivated (e.g., stock images), the effect is also diminished. This research has important implications for the literature on human-AI-collaboration, research on authenticity, and the ongoing policy debate regarding the transparency of algorithmic presence.

1. Introduction

Visual art is the endpoint of a creative process, and therefore knowledge of how a piece of art is made has a profound effect on how audiences think and feel about it (Dutton, 2003, 2009; Newman & Bloom, 2012). The creative process is a sequence of actions that can be broadly categorized as idea generation and implementation (Botella et al., 2018). Suppose you visit a museum and learn that an artist collaborated with artificial intelligence to create her work. You read that the idea for the painting did not come entirely from the artist's inner feelings and experiences, but was the result of a brainstorming session with artificial intelligence. The artist merely interpreted the idea artistically and painted it. Or imagine if an artist had the idea for a work of art, but the arrangement of the image was generated by an AI, and the artist simply painted it. Although both stories are fictional, the possibility of an artist using generative artificial intelligence in his or her work is more than feasible. Modern text-to-image generation systems such as OpenAI's DALL-E, Midjourney or Adobe Firefly are capable of translating a text prompt into an image and generating many possible implementations of an idea in a matter of seconds (Smith et al., 2023). Midjourney was recently used to win a fine art competition (Harwell, 2022). On the other hand, chatbots (e.g. ChatGPT or Bard) are capable of providing or brainstorming novel ideas that are worth pursuing (Memmert & Tavanapour, 2023). Discussion with such a system can inspire artists to realize a particular idea in a particular style. Artists such as David Young, Mike Tyka, Tom White and Daniel Ambrosi are already utilizing artificial intelligence. Young, for example, trains generative models on his own images and then has them create new images that reflect the machine's view of the world (www.davidyoung.art). Ambrosio uses a modified version of Google's DeepDream to augment his images. These so-called "dreamscapes" are based on his photographs, which the AI fills with an exceptionally high level of detail (www.danielambrosi.com/Portfolio/Dreamscapes-Behind-the-Scenes/).

How would the audience's evaluation of an artist's work and of the artist himself change if the audience was aware that the work was co-created with AI? There is a lack of research investigating perceptions of co-created visual art and, in particular, whether the disclosure of AI involvement at various stages of the creative production process affects

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the viewer's perception of the artwork and the artist. This is the focus of the present article. In addition, I seek to elucidate the mechanisms underlying these effects and their boundary conditions.

Users often feel reluctant and uncomfortable using AI ("algorithm aversion"; see Dietvorst et al., 2015; Mahmud et al., 2022 for a review), especially in situations that require emotion and involve subjectivity (Castelo et al., 2019; Waytz & Norton, 2014). In the realm of art production viewers tend to exhibit a preference for human-made art once the source is disclosed (Chamberlain et al., 2018; Köbis & Mossink, 2021; Millet et al., 2023). While people generally prefer human involvement, human-machine collaborations are typically viewed more positively than artificial agents acting on their own (Hitsuwari et al., 2023; Kern et al., 2022). I extend this stream of research by moving beyond the dichotomous characterization of art produced solely by AI (automation) versus art produced solely by humans, and instead focus on the collaboration between human artists and AI during two different stages of the creative process: ideation (i.e., finding an initial idea, getting inspired) and implementation (i.e., finding the layout and composition for the final painting). By connecting the existing literature on generative AI with the literature on creative control, authenticity, and novelty, this research deepens our understanding of the mechanisms and boundary conditions underlying the perception of AI-co-created artifacts. In line with recent research, I find that art produced by a human artist receives greater recognition and liking than art that was created with the assistance of AI. These effects are driven by perceptions of greater authenticity which overcompensate perceived novelty. However, evaluations depend on the stage in which AI is being utilized: Employing AI-tools to come up with an idea is more acceptable than to implement an idea. The findings also show that an artist is less admired when he collaborates with AI. While artists who use AI are perceived as more creative, they forfeit authenticity. In addition, this research investigates how to compensate for authenticity when co-creating with AI and finds that revealing the amount of human labor is a viable strategy (see Experiment 2). Finally, the research shows that co-creation with AI is more acceptable in the context of art that is not considered high art, such as illustrations and stock images (see Experiment 3). From a practical standpoint, this research provides important insights for creative professions. When human labor will be complemented by artificial intelligence (see Brynjolfsson & Mitchell, 2017) it is essential to understand the implications for the reception of the final product and the changes that the social evaluation of the person involved in the process may face.

1.1. Generative artificial intelligence

Multimodal content generated by artificial intelligence has recently received considerable attention. Generative AI systems take a user instruction (a prompt) as input and produce content that satisfies the instruction. While unimodal models can only process a single type of modality, such as language or vision, and generate the same modality, multimodal models generate modalities by learning the connection and interaction between different data types (for example, image generation using text input). One of the more prominent systems based on text-to-text models are chatbots. A chatbot is a program that enables natural conversation between humans and computers through text-based interfaces. Chatbots can be used for brainstorming, information retrieval, self-education, or translation from one language to another. Chatbots such as ChatGPT are based on natural language generators (NLG) that generate language based on user input. GPT is an autoregressive decoder-based language model that uses self-attention mechanisms which generates fluent and coherent text over many paragraphs (Cao et al., 2023). While software developers could use chatbots to speed-up repetitive tasks such as writing of short functions or explaining code (Merow et al., 2023) artists could use these tools for idea generation, to brainstorm and to discover topics worth painting.

Most image generation applications are based on multimodal (text-to-image) models. Given a text command, they generate images that reflect the meaning of the command. These models typically have an encoder-decoder architecture, where the encoder is concerned with understanding language and a decoder focuses on image synthesis (Cao et al., 2023). A GAN (generative adversarial network, Goodfellow et al., 2014) consists of two competing artificial neural networks, where one is a generator network trained to produce images and the other is a discriminator network trained to distinguish between real images and those produced by the first network. Iteratively, the generator network produces higher quality images that can fool the discriminator network (Frolov et al., 2021). AI art generators, such as OpenAI's DALL-E−2 and Midjourney, can generate realistic static images from a natural language description (openai.com/dall-e−2). These systems allow users to generate novel images in specific styles, which could mimic specific painting techniques or create entirely new compositions. For example, a user could request a Picasso-style painting. A software specifically designed for creative content creators is Adobe Firefly (firefly.adobe.com). It allows users to adjust content type (art vs. photo), style, lighting, and tone (Adobe, 2023). An artist could start with her own idea and ask for different implementations of a subject in a matter of seconds. If desired, the results could be combined in novel and unique ways.

1.2. Perception of the artifact

Previous research has focused on a) whether viewers can identify AI-generated work, and b) how they evaluate it. The majority of studies concentrate on entirely AI-generated art (full-automation), and do not focus on art that has been created as a collaboration between artist and machine (augmentation).

The literature indicates that individuals encounter difficulties identifying AI-generated art (e.g. Gangadharbatla, 2022; Köbis & Mossink, 2021; Ragot et al., 2020; Samo & Highhouse, 2023). Ragot et al. (2020) discovered that humans can detect machine-generated artworks with an accuracy of only 56%, which is almost equivalent to chance. In addition, individuals tend to dislike art produced by machines (Chamberlain et al., 2018; Köbis & Mossink, 2021; Millet et al., 2023). This finding is consistent with the extant work on algorithms that shows that users are reluctant to rely on algorithms for tasks that appear to be subjective and symbolic (Castelo et al., 2019; Granulo et al., 2021). During a blind test comparing human- and machine-generated visual art, individuals appear to experience more positive emotions when viewing art created by humans (Samo & Highhouse, 2023). Art produced by an artificial process on the other hand, is perceived as less impressive (Millet et al., 2023).

When people evaluate art, including still works like paintings, they view them as the outcome of a creative procedure. Therefore, the worth and perceived artistic excellence of artworks depend on the observation of the realized product and inferences about the process employed to create it (Dutton, 2003). A number of related studies illustrate this view. The value attributed to art is derived from the creative act and the degree of direct physical contact with the artist (Newman & Bloom, 2012), as artworks serve as extensions of their creators and embody their essence (Newman et al., 2014). Artworks that are closer to their creator are more valuable (Smith et al., 2016). Similarly, the "effort heuristic" suggest that the amount of perceived effort involved in creating an artwork serves as a cognitive shortcut for evaluating its quality (Jucker et al., 2014; Kruger et al., 2004) and handmade items are more attractive because they literally contain love (Fuchs et al., 2015). The extent to which the same person was responsible for the creative process determines the degree of creative authenticity that can be attributed to an artifact. Artworks with more creative control by the artist are more authentic and acclaimed (Valsesia et al., 2016).

Taken together, art requires the use of skill to express human experience and is not primarily driven by commercial motives (Hagtvedt & Patrick, 2008, p. 380). The use of technology in the creative process can be perceived as artificial or fake, rendering the product less meaningful

(Kirk et al., 2009). When revealing the involvement of AI in the creation of art, viewers tend to respond negatively (Millet et al., 2023; Raj et al., 2023). Based on these previous findings, I argue that artworks produced in collaboration with AI are less liked, less recognized, and less likely to be categorized as art.

In this research the main mechanism explaining why co-created art is judged less favorably is authenticity, which is an important construct in the evaluation of cultural products (Kreuzbauer & Keller, 2017; Valsesia et al., 2016). Two prerequisites are used by audiences when assessing authenticity: producer motivation and creative control over the process (Bhattacharjee et al., 2014; Jung et al., 2023; Kreuzbauer et al., 2015; Valsesia et al., 2016; Verhaal & Dobrev, 2022; Wang et al., 2023). I argue that artists who use AI during the ideation stage violate audience expectations of authenticity because their motives are questioned (Silver et al., 2021), while those who use AI during implementation violate expectations of authenticity because they relinquish creative control (see Valsesia et al., 2016). Using AI tools to brainstorm ideas for inspiration implies that the idea is not originally inspired by the artist's own inner feelings and experiences or may be tainted by the input from the AI. As art should reflect the artist's personal experience and remain independent of commercial motives (Bhattacharjee et al., 2014; at least for high art, see Fisher, 2013), the act of creation seems to be inspired by the wrong motivations and the work is not what it claims to be (Silver et al., 2021). In other words, collaborating with these tools can be seen as a corruption of the intended motives, leading to a perception of inauthenticity. Using a tool in the implementation phase, such as an AI image generator like Midjourney, to obtain different layouts of an idea means a reduction in creative control over the process and the final product. Handing over part of the responsibility for implementing visual art to AI distances the final product from the artist's original vision and reduces the perception of creative control, and thus authenticity – the perception that the final product is actually a true representation of the creator's original vision (Valsesia et al., 2016).

Viewers, professional and laypeople alike, value novelty in art such as new techniques and the modification of existing paradigms (Chen, 2009). In the western world, novelty is seen as a prerequisite for creativity (Kharkhurin, 2014). Artists have frequently modified their methods of producing art. For instance, Jackson Pollock invented a dripping and pouring technique while painting on the floor and in Cubism artists started to paint objects from multiple angles to give viewers the impression of viewing them from different perspectives (Yokochi & Okada, 2021). Artists have been using technology to create art for decades and the use of technology such as photography, video, and computers is referred to as digital art (Paul, 2002). Laposky combined art and computing in the early 1950s by manipulating electronic signals and photographing them in waveforms using an oscilloscope (Hope & Ryan, 2014). While painting was typically done with fingers or brushes, the advent of computer technology allowed artists to use electronic drawing as early as 1975 with SuperPaint. Today, portable technologies such as tablets with pens are used to sketch, draw, and even create entire paintings (Nappi, 2013). I argue that AI represents a new kind of resource for artists that can bring innovation to the creative process. Like digital pencils or painting software, AI does not mark the end of art. Instead, it offers a new creative space that viewers can appreciate when the process of creation is revealed. Some artists, such as Daniel Ambrosi, who use AI to create what was not possible before, are being praised for their innovation in using technological advances.

In addition, past work has shown that effort estimation is an important predictor of value in art. The effort heuristic proposes that laypeople would rate a piece of art as higher quality and like it more if they knew that the artist spent more time and effort to produce it (e.g., Kruger et al., 2004). This effect may occur because viewers believe that more resources were used, or because more effort implies higher artistic performance (Newman & Bloom, 2012). People readily make attributions about why an actor uses technology. For example, when asked what motivates companies to use chatbots in customer service, respondents often emphasized cost savings and self-interest motivations (Castelo, Boegershausen, Hildebrand, & Henkel, 2023). Using AI in the ideation or implementation stages of artistic creations can objectively reduce the artist's effort. Generative AI can quickly generate layouts and possible implementations of an image, and the tool's results can serve as a starting point for the artist's painting, significantly reducing the amount of effort and time required.

Thus, the central hypotheses of this paper are that (a) viewers evaluate art co-created with AI less favorably, like it less, consider it less worthy of recognition and less belonging to the category "art", (b) these effects are driven by perceptions that co-created art is less authentic and requires less effort on the part of the artist, (c) but co-created art is also perceived as more novel, which partially mitigates the effects of authenticity and effort perception.

1.3. *Perception of the artist*

When describing artists, laypeople and professionals often express admiration. For example, the Getty Museum's primer on Michelangelo is full of praise for his ingenious compositions and exceptional skill (www.getty.edu/art/exhibitions/michelangelo_drawings). Admiration is an other-praising emotion toward people who achieve excellence and is felt when observing exceptional skill or talent, such as the creative achievement of an artist (Algoe & Haidt, 2009; Matsumoto & Okada, 2021). Admiration must be distinguished from awe and fame. Awe is evoked by an ability so extraordinary that it is almost impossible to comprehend (Keltner & Haidt, 2003), while fame refers to professional success and is the result of performance in the art market (Banerjee & Ingram, 2022). Admiration inspires people to learn and improve from their role models, and it confers prestige and often awards to those who elicit admiration (Henrich & Gil-White, 2001; Immordino-Yang, 2011; Onu et al., 2016).

In the course of this section, I will argue that perceived creativity and authenticity connect collaboration with AI in the creative process and admiration felt towards an artist. Creativity is a skill highly valued in the art domain. It is challenging to make objective inferences about creativity without information about the target's past actions (Hehman et al., 2017). Therefore, the evaluation of creations by the target facilitates the formation of impressions about their creativity (Katz et al., 2022). The use of AI in the creative process allows for two potential inferences. The initial implication is that the use of tools is creative as it alters the paradigm of creating art. Examples of this approach are illustrated by artists such as Pollock and Laposky, who pushed beyond existing creative boundaries to approach their work from new perspectives. Besides, the use of AI in creative work involves a high degree of creative input from the technology, which can generate ideas based on learned patterns, so that the apparent creativity of the artifact may no longer be attributed to the artist. I argue that as long as AI is new to the field of art, inferences will be more likely to gravitate toward the first category of inferences, and that art created with AI will lead to higher ratings of artists' creativity.

Moulard et al. (2014) define an authentic artist as one who is motivated by intrinsic passion and commitment for his work, rather than being driven primarily by extrinsic, commercial motives. Being satisfied with the activity itself and using it as a medium for self-expression or skill refinement is considered the most authentic approach for an artist. On the other hand, aiming to be commercially successful by painting does not align with this notion (Moulard et al., 2015; Ryan & Deci, 2000). It is difficult for perceivers to know how passionate someone is about their work. Nevertheless, perceivers tend to evaluate an artist based on available information, such as the process the artist used to create his or her work. AI tools rely on machine learning algorithms that stochastically combine data to generate new outcomes, without relying on emotions or personal experiences in the process. Using tools that suggest ideas or layouts tends to diminish the significance of personal inspiration and passion for art. Brainstorming ideas with a chatbot can signal a lack of vision and lead to suspicion of the artist's motives. Similarly, using artificial intelligence to create layouts can imply a lack of enthusiasm in constructing the work to reflect a personal vision (see also Valsesia et al., 2016). Research in social psychology has found that admiration is evoked when a target is perceived as competent and warm (Fiske et al., 2007). Authenticity and interpersonal warmth are closely related because warmth refers to the perception of good intentions and genuineness of motives (Berger & Barasch, 2018; Tang et al., 2022). Therefore, authentic targets are perceived as warmer than inauthentic ones (Tang et al., 2022). The competence dimension is concerned with whether a target is capable of pursuing his or her intentions and encompasses traits such as intelligence, skill, and creativity (Cuddy et al., 2008). Targets described as more creative are perceived as more competent, particularly when depicted as belonging to the arts domain (Bonetto et al., 2020). Based on the arguments, the hypotheses are that (a) viewers evaluate artists who use AI in the creation process as less admirable and that (b) these effects are driven by perceptions of creativity and authenticity (see Table 1).

2. Experiment 1: initial test of the proposed effects

2.1. Participants

Two hundred eighty participants completed the study on Prolific Academic in exchange for an average of 1.20 $. Inclusion criteria was completion of at least 10 previous studies. Two participants were excluded from further analysis because they indicated that they had not paid attention, leading to a final sample size of two hundred seventy-eight participants (188 female, 87 male, three other or declined to respond; age: M = 30.66, SD = 9.10, Min = 18, Max = 71). This sample size gives a power of > .95 to detect a two-tailed medium effect size (Cohen's f = 0.25, calculated with G*Power 3.1.9.7).

Table 1
Overview of hypotheses, experiments, and results.

Hypotheses	Supported?	Results
Experiment 1: Initial test of the proposed effects (N = 280, Prolific)		
Evidence that the stage of co-creation does matter for evaluation of artwork and artist		
Co-created *artworks* are …		Co-created artworks are perceived as more innovative, but also as less effortful and authentic. Authenticity is the primary factor influencing evaluations. Co-creation is particularly detrimental during the implementation stage.
– liked less	✓	
– considered less worthy of recognition	✓	
– less belonging to the category "art"	✓	
Effects are mediated by perceptions of …		
– authenticity	✓	
– effort	✓	
– novelty	✓	
Artists using AI in the creation process are perceived as …		Artists are most admired when they do not use AI at all. Using AI, especially during ideation, makes them seem more creative. This effect is offset by reduced attribution of authenticity.
– less admirable	✓	
Effects are mediated by perceptions of …		
– creativity	✓	
– authenticity	✓	
Experiment 2: Increasing authenticity while creating with AI (N = 120, Prolific)		
Evidence of involvement and vision as ways to restore authenticity when collaborating with AI		
Perceptions of artness and recognition can be enhanced by …		Signaling artist involvement by training the AI on a curated set of the artist's paintings (and communicating a vision for the application of AI) increases the appreciation of an artwork.
– signaling involvement	✓	
– signaling involvement and vision	✓	
Experiment 3: Art versus non-art (N = 160, Prolific)		
Evidence of art type (art vs. art-like) moderating the effects of co-creation on outcomes		
The effects of co-creation on liking, recognition, and artness are moderated by intentions to create art vs. art-like objects.	✓	The effects of co-creation on outcomes are more detrimental when the artist intends to create art vs. art-like artifacts.

2.2. Procedure

The use of AI during the ideation and implementation stage of the creation of a painting was manipulated. The study used a 2 (ideation: artist vs. AI) × 2 (implementation: artist vs. AI) between-participants design. All participants saw a landscape painting and were asked to evaluate the painting and the artist. The image of the painting was sourced from a stock-image platform (see Appendix). The landscape category was chosen for two reasons. First, landscape images are popular with the general audience (Fekete et al., 2022). Second, because I intended to use generative AI to generate images in Experiment 2 and 3 a landscape image was more suitable since AI is still more adept at generating landscapes than other categories, ensuring a realistic image without obvious signs of synthetic generation (Hertzmann, 2020). Basic information about the painting was provided in all conditions (creation date, artist name, and name of the painting; the information from the original image has been modified to better suit the experiment). Participants were randomly assigned to one of the four conditions. Participants in the ideation condition read either that the artist had the inspiration for the idea (artist) or that she brainstormed with a chatbot named "Create" to help her come up with an idea for the painting (AI). To manipulate implementation participants either read that the artist used her imagination to design the layout of the painting (artist) or that she used an AI-tool called "Implema" that provided multiple compositions for the painting that the artist then arranged (AI). In the conditions were the artist collaborated with AI-tools an image of the tool's interface was shown to participants (see Appendix 4 for the full stimuli). The artist painted the landscape using oil on canvas in all conditions and the painting was the same for all respondents.

2.3. Measures

Participants first completed two manipulation checks ("The artist used "Create" to find the idea for the painting."; "The artist used "Implema" to generate different layouts for the painting."; measured on 7-point Likert scales anchored in 1 = "*not at all*" to 7 = "*very much*"). Next, I measured recognition (Valsesia et al., 2016) and aesthetic liking (Fuchs et al., 2015), creative authenticity (Valsesia et al., 2016), novelty (inspired by Moldovan et al., 2011), expected effort (Kruger et al., 2004), artists' creativity (Moulard et al., 2014) and authenticity (Katz et al., 2022) as well as evaluations of the artist (admiration; Fiske & Dupree, 2014; Sweetman et al., 2013). Finally, participants provided demographic information and answered an attention check: "Do you feel that you paid attention, avoided distractions, and took the survey seriously?" Participants selected one of the following responses: (1) no, I was distracted; (2) no, I had trouble paying attention; (3) no, I didn't take the study seriously; (4) no, something else affected my participation negatively; or (5) yes. Participants were informed that their responses to the check would not affect their payment (Stanley et al., 2020).

To ensure sound psychometric properties of the scales a confirmatory factor analysis was conducted (CFA, estimator MLR in the R-library lavaan [Rosseel, 2012]). The analysis shows appropriate model fit (Chi-squared = 480.41, df = 289, CFI = 0.963, TLI = 0.955, RMSEA = 0.049, SRMR = 0.047). Following Fornell and Larcker's (1981) recommended procedure there were no discriminant validity concerns (see Appendix 1 for items and results).

2.4. Manipulation checks

An independent samples *t*-test revealed that participants recognized that the artist used an AI-tool to brainstorm in the ideation co-creation condition (M = 6.60, SD = 0.85) versus the condition were the artist came up with the idea by herself (M = 2.64, SD = 2.03), $t(276) = 21.33$, $p < .001$, Cohen's d = 2.56. A second *t*-test revealed that participants recognized that the artist used an AI-tool to generate implementations of the painting in the implementation co-creation condition (M = 6.47, SD

= 1.03) versus the condition were the artist designed the layout by herself ($M = 2.20$, $SD = 1.87$, $t(276) = 23.57$, $p < .001$, Cohen's $d = 2.83$).

2.5. Main and interaction effects on outcomes

Recognition. I conducted a 2 (ideation) × 2 (implementation) analysis of variance (ANOVA) to analyze participants' evaluations of the painting. The ANOVA revealed no significant main effect of ideation ($M_{AI} = 3.47$, $SD = 1.47$ vs. $M_{artist} = 3.38$, $SD = 1.40$; $F(1, 274) = 0.246$, $p = .62$) but of implementation ($M_{AI} = 3.15$, $SD = 1.45$ vs. $M_{artist} = 3.70$, $SD = 1.37$; $F(1, 274) = 10.543$, $p < .01$, $\eta^2p = .04$). The interaction between ideation and implementation was not significant.

Aesthetic liking. Again, I conducted a 2 (ideation) × 2 (implementation) ANOVA to analyze participants' liking of the painting. The ANOVA revealed no significant main effect of ideation ($M_{AI} = 7.21$, $SD = 2.01$ vs. $M_{artist} = 7.12$, $SD = 2.28$; $F(1, 274) = 0.127$, $p = .72$) but of implementation ($M_{AI} = 6.69$, $SD = 2.27$ vs. $M_{artist} = 7.64$, $SD = 1.90$; $F(1, 274) = 14.78$, $p < .001$, $\eta^2p = .05$). Moreover, I found a significant interaction effect ($F(1, 274) = 5.43$, $p = .02$, $\eta^2p = .02$): when the idea originates from the artist implementation by AI leads to lower liking ($M_{AI\text{-}implementation} = 6.35$, $SD = 2.32$ vs. $M_{artist\text{-}implementation} = 7.90$, $SD = 1.96$). This reduction in liking is not found when the idea also comes from AI.

Artness. A 2 (ideation) × 2 (implementation) ANOVA revealed no significant main effect of ideation ($M_{AI} = 7.30$, $SD = 2.49$ vs. $M_{artist} = 7.07$, $SD = 2.50$; $F(1, 274) = 0.743$, $p = .39$) but of implementation ($M_{AI} = 6.29$, $SD = 2.58$ vs. $M_{artist} = 8.10$, $SD = 2.03$; $F(1, 274) = 42.77$, $p < .001$, $\eta^2p = .14$). The interaction effect was marginally significant on the $p = .10$ level ($F(1, 274) = 3.62$, $p = .06$, $\eta^2p = .01$).

Admiration. Utilizing another ANOVA I found a significant main effect of ideation ($M_{AI} = 3.89$, $SD = 1.49$ vs. $M_{artist} = 4.31$, $SD = 1.53$; $F(1, 274) = 5.88$, $p = .02$, $\eta^2p = .02$) and of implementation ($M_{AI} = 3.63$, $SD = 1.43$ vs. $M_{artist} = 4.57$, $SD = 1.47$; $F(1, 274) = 29.90$, $p < .001$, $\eta^2p = .10$) on admiration. Additionally, the interaction effect was also significant ($F(1, 274) = 4.35$, $p = .04$, $\eta^2p = .02$): implementation by the artist is more admired when the idea stems from the artist than when it was brainstormed with AI (see Table 2 and Fig. 1).

2.6. Main and interaction effects on mediators

Next, I analyzed the effects of the independent variables on the potential mediators.

Authenticity. The ANOVA reveals a main effect of ideation ($M_{AI} = 3.47$, $SD = 1.40$ vs. $M_{artist} = 4.52$, $SD = 1.58$; $F(1, 274) = 49.19$, $p < .001$, $\eta^2p = .15$), a main effect of implementation ($M_{AI} = 3.19$, $SD = 1.22$ vs. $M_{artist} = 4.80$, $SD = 1.50$; $F(1, 274) = 115.64$, $p < .001$, $\eta^2p = .30$), and an interaction effect ($F(1, 274) = 7.14$, $p < .01$, $\eta^2p = .03$): The effect of implementation by the artist is stronger when the idea originates from the artist.

Novelty. I find a main effect of ideation ($M_{AI} = 5.14$, $SD = 1.28$ vs. $M_{artist} = 4.01$, $SD = 1.77$; $F(1, 274) = 45.34$, $p < .001$, $\eta^2p = .14$), a significant main effect for implementation ($M_{AI} = 5.05$, $SD = 1.39$ vs. $M_{artist} = 4.23$, $SD = 1.75$; $F(1, 274) = 30.63$, $p < .001$, $\eta^2p = .10$), and an interaction effect ($F(1, 274) = 34.64$, $p < .001$, $\eta^2p = .11$).

Effort. A main effect of ideation ($M_{AI} = 4.05$, $SD = 1.39$ vs. $M_{artist} = 4.43$, $SD = 1.49$; $F(1, 274) = 6.00$, $p = .02$, $\eta^2p = .02$), a significant main effect for implementation ($M_{AI} = 3.59$, $SD = 1.30$ vs. $M_{artist} = 4.89$, $SD = 1.29$; $F(1, 274) = 72.17$, $p < .001$, $\eta^2p = .21$), but no interaction effect ($F(1, 274) = 1.53$, $p = .22$) was found.

Artist creativity. I found a main effect of ideation ($M_{AI} = 4.37$, $SD = 1.51$ vs. $M_{artist} = 3.93$, $SD = 1.40$; $F(1, 274) = 6.48$, $p = .01$, $\eta^2p = .02$), a significant main effect for implementation ($M_{AI} = 4.32$, $SD = 1.46$ vs. $M_{artist} = 3.98$, $SD = 1.47$; $F(1, 274) = 3.90$, $p = .049$, $\eta^2p = .01$), and an interaction effect ($F(1, 274) = 1.53$, $p = .02$, $\eta^2p = .02$): implementation by the artist leads to lower levels of creativity when the idea stems from the artist then when it stems from a collaboration with AI.

Artist authenticity. A main effect of ideation ($M_{AI} = 3.96$, $SD = 1.56$ vs. $M_{artist} = 4.52$, $SD = 1.51$; $F(1, 274) = 10.65$, $p < .01$, $\eta^2p = .04$), a significant main effect for implementation ($M_{AI} = 3.68$, $SD = 1.47$ vs. $M_{artist} = 4.79$, $SD = 1.45$; $F(1, 274) = 42.20$, $p = < .001$, $\eta^2p = .13$), and an interaction effect ($F(1, 274) = 4.44$, $p = .04$, $\eta^2p = .02$) was found: the effect of artist implementation is stronger when the idea stems from the artist versus when it is a result of collaboration with AI ($M_{AI} = 4.34$, $SD = 1.43$ vs. $M_{artist} = 5.53$, $SD = 1.32$).

2.7. Moderated mediation analyses

Recognition. I ran a moderated mediation analysis (PROCESS Model 7, 10,000 bootstrapped samples; Hayes, 2017) with recognition as the dependent variable, implementation (−1 = artist, 1 = AI) as the independent variable, ideation (−1 = artist, 1 = AI) as the moderator, and authenticity, novelty, and effort as the mediators. As predicted, I found a significant moderated mediation effect for authenticity (index of

Table 2
Main and interaction effects Experiment 1.

		Evaluation of the artifact			Evaluation of the artist	
		Mediators				
Idea	Imple	Authenticity	Novelty	Effort	Artist creativity	Artist authenticity
AI	AI	2.87 (1.23)	5.12 (1.40)	3.49 (1.32)	4.34 (1.52)	3.58 (1.61)
AI	Artist	4.08 (1.29)	5.16 (1.17)	4.61 (1.24)	4.40 (1.51)	4.34 (1.43)
Artist	AI	3.52 (1.12)	4.97 (1.38)	3.68 (1.29)	4.31 (1.41)	3.78 (1.31)
Artist	Artist	5.53 (1.33)	3.05 (1.59)	5.18 (1.29)	3.55 (1.30)	5.26 (1.32)
				Effects ANOVA		
Ideation		*F(1,274) = 49.19, p < .001*	*F(1,274) = 45.34, p < .001*	*F(1,274) = 6.00, p = .02*	*F(1,274) = 6.48, p = .01*	*F(1,274) = 10.65, p < .01*
Implementation		*F(1,274) = 115.64, p < .001*	*F(1,274) = 30.63, p < .001*	*F(1,274) = 72.17, p < .001*	*F(1,274) = 3.90, p = .049*	*F(1,274) = 42.20, p = < .001*
Interaction		*F(1,274) = 7.14, p < .01*	*F(1,274) = 34.64, p < .001*	F (1,274) = 1.53, p = .22	*F(1,274) = 1.53, p = .02*	*F(1,274) = 4.44, p = .04*

		Outcomes			
Idea	Imple	Recognition	Liking (10-point)	Artness (10-point)	Admiration
AI	AI	3.33 (1.63)	7.01 (2.19)	6.66 (2.79)	3.60 (1.56)
AI	Artist	3.61 (1.28)	7.40 (1.81)	7.96 (1.95)	4.19 (1.36)
Artist	AI	2.98 (1.22)	6.35 (2.32)	5.90 (2.30)	3.66 (1.30)
Artist	Artist	3.80 (1.46)	7.90 (1.96)	8.25 (2.12)	4.96 (1.48)
			Effects ANOVA		
Ideation		F (1,274) = 0.25, p = .62	F (1,274) = 0.13, p = .72	F (1,274) = 0.74, p = .39	*F(1,274) = 5.88, p = .02*
Implementation		*F(1,274) = 10.54, p < .01*	*F(1,274) = 14.78, p < .001*	*F(1,274) = 42.77, p < .001*	*F(1,274) = 29.90, p < .001*
Interaction		*F(1,274) = 2.58, p = .11*	*F(1,274) = 5.43, p < .05*	F (1,274) = 3.62, p = .06	*F(1,274) = 4.35, p < .05*

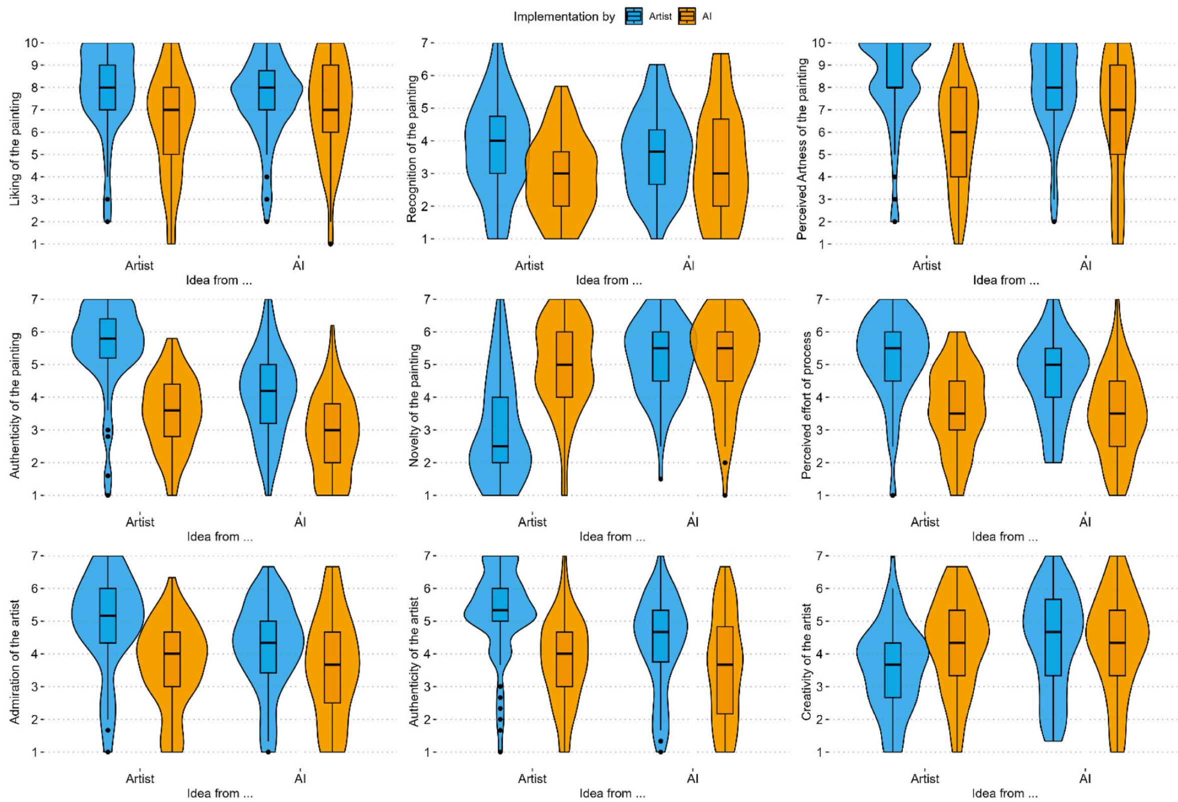


Fig. 1. Main and interaction effects Experiment 1: The effects of collaborating with AI in different stages of the art creation process.

moderated mediation: B = 0.17, 95% CI = [0.04, 0.32]), and for novelty (B = −0.30, 95% CI = [−0.43, −0.18]) but not for effort. When the idea for the painting originates from the artist, the indirect effect of implementation through authenticity was larger (B = −0.43, 95% CI = [−0.59, −0.29]) than when the idea was brainstormed with AI (B = −0.26, 95% CI = [−0.38, −0.16]), suggesting that AI-implemented paintings are even less recognized when the idea originates from the artist. When the idea for the painting originates from the artist, the indirect effect of implementation by AI on recognition through novelty was significant and positive (B = 0.29, 95% CI = [0.18, 0.41]) but not when the idea was brainstormed with AI (B = −0.006, 95% CI = [−0.07, 0.06]).

Liking. Next, I ran another moderated mediation analysis (PROCESS Model 7, 10,000 bootstrapped samples; Hayes, 2017) with liking as the dependent variable, implementation (−1 = artist, 1 = AI) as the independent variable, ideation (−1 = artist, 1 = AI) as the moderator, and authenticity, novelty, and effort as the mediators. As predicted, I found a significant moderated mediation effect for authenticity (index of moderated mediation: B = 0.16, 95% CI = [0.03, 0.33]), and for novelty (B = −0.27, 95% CI = [−0.42, −0.12]) but not for effort. When the idea for the painting originates from the artist, the indirect effect of implementation through authenticity was significantly larger (B = −0.40, 95% CI = [−0.64, −0.17]) than when the idea was brainstormed with AI (B = −0.24, 95% CI = [−0.40, −0.10]). When the idea originates from the artist, the indirect effect of implementation by AI through novelty was significant and positive (B = 0.26, 95% CI = [0.12, 0.41]) than when the idea was brainstormed with AI (B = −0.006, 95% CI = [−0.07, 0.06]), suggesting that AI use in the implementation phase increases liking via novelty only when the idea stems from the artist.

Artness. Another moderated mediation analysis (PROCESS Model 7, 10,000 bootstrapped samples; Hayes, 2017) with artness as the dependent variable was conducted. As predicted, the results show a significant moderated mediation effect for authenticity (index of moderated mediation: B = 0.24, 95% CI = [0.05, 0.44]), and for novelty (B = −0.24, 95% CI = [−0.41, −0.10]) but not for effort. When the idea for the painting originates from the artist, the indirect effect of implementation through authenticity was again significantly larger (B = −0.59, 95% CI = [−0.84, −0.37]) than when the idea was brainstormed with AI (B = −0.36, 95% CI = [−0.55, −0.20]). When the idea for the painting originates from the artist, the indirect effect of implementation through novelty was significant and positive (B = 0.24, 95% CI = [0.10, 0.39]) compared to when the idea was brainstormed with AI (B = −0.006, 95% CI = [−0.06, 0.05]).

Admiration. Using PROCESS Model 7 with 10,000 bootstrapped samples (Hayes, 2017) I analyzed admiration as the dependent variable, implementation (−1 = artist, 1 = AI) as the independent variable, ideation (−1 = artist, 1 = AI) as the moderator, and artist authenticity and artist creativity as the mediators. As predicted, I found a significant moderated mediation effect for artist authenticity (index of moderated mediation: B = 0.22, 95% CI = [0.01, 0.43]), and for artist creativity (B = −0.09, 95% CI = [−0.18, −0.02]). When the idea for the painting originates from the artist, the indirect effect of implementation through authenticity was smaller (B = −0.23, 95% CI = [−0.39, −0.08]) than when the idea was brainstormed with AI (B = −0.46, 95% CI = [−0.61, −0.30]). When the idea for the painting originates from the artist, the indirect effect of implementation through creativity was significant and positive (B = 0.09, 95% CI = [0.03, 0.15]) compared to when the idea was brainstormed with AI (B = −0.008, 95% CI = [−0.07, 0.05]), suggesting that AI use in the implementation phase increases recognition only when the idea stems from the artist.

2.8. Discussion

Experiment 1 confirms all hypotheses: Co-created art is less liked, less recognized, and less likely to be categorized as art. Although perceived as more innovative, it is also seen as less authentic, which is the primary factor influencing evaluations. In addition, the findings indicate that co-creation is especially detrimental during the implementation phase of a project.

However, the manipulation of the implementation stage was rather narrow in that the artist created paintings using an off-the-shelf product, which requires minimal input (i.e., a textual description of the desired image). This scenario is realistic in the sense that artists now have wide access to these kinds of tools. I aim to dive deeper and understand how artists could mitigate loss of authenticity during co-creation in the implementation stage. Authenticity requires creative control (Valsesia et al., 2016) and intrinsic motivation (Bhattacharjee et al., 2014; Verhaal & Dobrev, 2022). Revealing the amount of involvement over the creative process could be achieved by controlling the AI itself, for instance, by steering the image generation process using a curated training dataset based on the artist's own work (see Hemment et al., 2023) or by tweaking the algorithms according to the artist's needs. Authenticity also relies on the attribution of intrinsic motivation. Signaling passion and enthusiasm for a craft is a possible way of encouraging the attribution of intrinsic motivations (Jung et al., 2023), and artists might communicate a vision to signal intentions rather than leaving interpretation to the perceiver, who might misattribute the use of AI as motivated by extrinsic, commercial forces. For example, an artist might be intrinsically motivated to use AI to understand whether it can create visual abstractions of images that are recognizable to other AIs and humans (see White, 2019). Communicating this interest to the audience may increase authenticity through attributions of intrinsic motivation (Jung et al., 2023). Therefore, in Experiment 2, I investigate how signaling involvement in the implementation process (i.e., by training the tool on curated images) and communicating intrinsic motivation via a vision (i.e., using AI to combine human and machine views of nature) improves perceived authenticity compared to a control condition (i.e., using an off-the-shelf solution for image generation).

3. Experiment 2: increasing authenticity while creating with AI

3.1. Participants

One hundred twenty participants completed the study on Prolific Academic in exchange for an average of 1.20 $. Inclusion criteria was completion of at least 10 previous studies. Four participants were excluded from further analysis because they indicated that they had not paid attention, leading to a final sample size of one hundred and sixteen participants (30 female, 85 male, one declined to respond; age: M = 30.45, SD = 8.79, Min = 18, Max = 72).

3.2. Procedure

Participants were randomly assigned to one of three conditions: control vs. involvement vs. involvement & vision (abbrev. vision). Participants in the control condition read about an artist who uses AI to create his paintings. Following a three-step approach the artist prompts a commercially available AI image generator to generate landscape images. He selects an appropriate image and paints it on canvas. In the involvement condition, participants read the same scenario as in the control condition but learn that the artist trains the AI using a curation of his own images. Participants in the vision condition read the same text as the involvement condition but with the additional information that the artist is motivated to see nature through the eyes of the machine to combine the human and the machine perspective (see Appendix for a detailed description of the stimuli and wording; images of the paintings were created using Adobe Firefly: firefly.adobe.com). Participants in all conditions were then asked to indicate perceptions of the paintings' authenticity, novelty, and effort, as well as liking, artness, and recognition using the same scales as in Experiment 1. Psychometric properties of the scales were tested using a confirmatory factor analysis (CFA, estimator MLR in the R-library lavaan [Rosseel, 2012]). The analysis shows acceptable model fit (Chi-squared = 105.416, df = 39, CFI = 0.906, TLI = 0.868, RMSEA = 0.121, SRMR = 0.056). Following Fornell and Larcker's (1981) recommended procedure I had to remove one item from the novelty scale to achieve discriminant validity (see Appendix 2 for items).

3.3. Manipulation checks

Participants indicated whether the AI was trained using (1 = images from the Internet vs. 10 = images from the artist) and whether the goal of the artist is (1 = unknown vs. 10 = known). An ANOVA revealed that participants recognized that the AI was trained with images from the artist in the involvement (M = 9.29, SD = 2.19) and vision conditions (M = 9.46, SD = 1.82) but not in the control condition (M = 2.13, SD = 2.04; F (2, 113) = 166.5, $p < .001$). The post-hoc test between control and involvement (Tukey-adjusted $p < .001$, $d = 3.38$) as well as control and vision (Tukey-adjusted $p < .001$, $d = 3.79$) was significant, while the test between involvement and vision was not (Tukey-adjusted $p = .93$, $d = 0.63$). Similarly, participants indicated that the artist's vision was known more so in the vision condition (M = 8.10, SD = 2.46) than in the involvement (M = 5.39, SD = 3.37) or the control condition (M = 6.21, SD = 3.66; F (2, 113) = 7.8, $p < .001$). Contrasts were significant only between vision and control (Tukey-adjusted $p < .05$, $d = 0.64$) and vision and involvement (Tukey-adjusted $p < .001$, $d = 0.92$) but not between control and involvement (Tukey-adjusted $p = .49$, $d = 0.24$).

3.4. Main effects

Four ANOVAs revealed a significant effect on authenticity (F (2, 113) = 9.1, $p < .001$), effort (F (2, 113) = 10.7, $p < .001$), recognition (F (2, 113) = 4.24, $p < .05$), and artness (F (2, 113) = 6.9, $p < .01$, see Fig. 2). Post-hoc tests revealed that participants find the artwork more authentic in the involvement (M = 3.81, SD = 1.42, Tukey-adjusted $p < .05$, $d = 0.56$) and the vision condition (M = 4.32, SD = 1.22, Tukey-adjusted $p < .001$, $d = 0.97$) compared to the control condition (M = 3.00, SD = 1.48). There was no difference between involvement and vision ($p > .05$). Participants perceived marginally more effort in the involvement (M = 4.03, SD = 1.30) than in the control condition (M = 3.37, SD = 1.33, Tukey-adjusted $p = .08$, $d = 0.50$) and significantly more effort in the vision condition (M = 4.77, SD = 1.37, Tukey-adjusted $p < .001$, $d = 1.04$) compared to the control condition. The difference between vision and involvement was also significant (Tukey-adjusted $p < .05$, $d = 0.56$). Concerning recognition, participants rated the painting higher in the vision (M = 4.06, SD = 1.49) compared to the control condition (M = 3.10, SD = 1.43, Tukey-adjusted $p < .05$, $d = 0.65$). The difference between the latter two conditions was not significant ($p > .05$). The same pattern of results emerged for artness where participants perceived the painting more as art in the vision condition (M = 7.97, SD = 2.15) compared to the control condition (M = 5.85, SD = 2.85, Tukey-adjusted $p < .01$, $d = 0.84$). However, the difference between involvement and vision was only marginally significant (Tukey-adjusted $p = .07$). No effects were found on novelty (F (2, 113) = 1.04, p = 36) and liking (F (2, 113) = 0.5, $p = .60$).

3.5. Mediation analysis

I aimed to examine if the effect of involvement and vision on liking, artness, and recognition was mediated by authenticity. I also included the mediators novelty and effort to test if the mediating role of authenticity was maintained when the influence of the other mediators were accounted for. As the independent variable has three levels, two dummy variables were specified (i.e., D1: comparing the control group and the involvement group and D2: comparing the vision group and the control group). I ran a parallel mediation analysis using model 4 of PROCESS (Hayes, 2017) with 10,000 resamples which revealed that the indirect effect of condition on recognition via authenticity was significant for both dummy variables (D1: B = 0.29, 95% CI = [0.05, 0.58]; D2: B = 0.47, 95% CI = [0.19, 0.81]). The analysis yielded similar results for

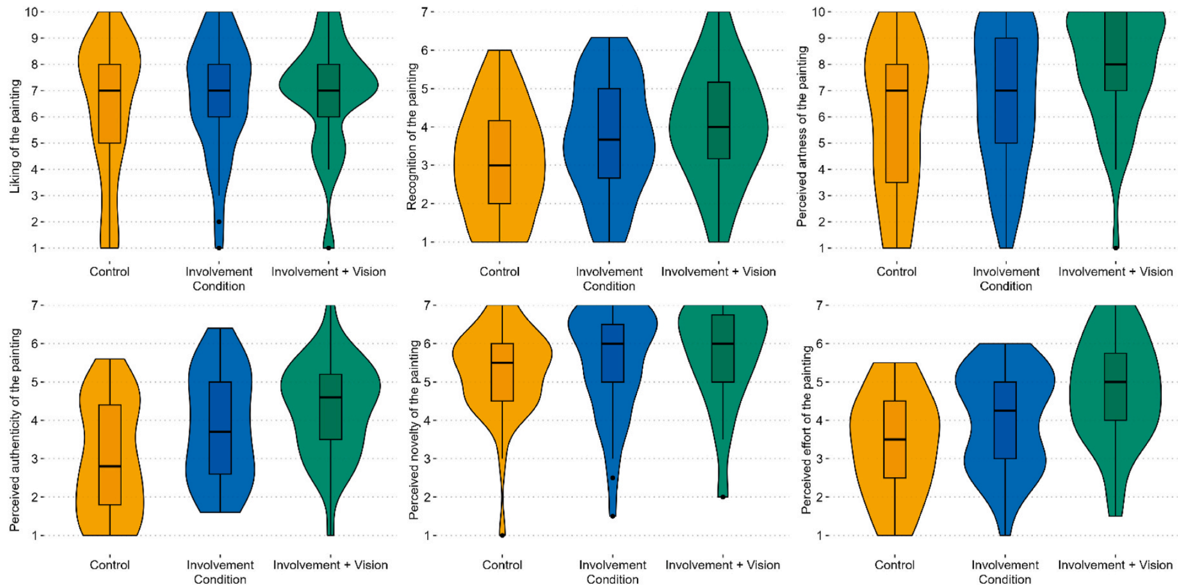


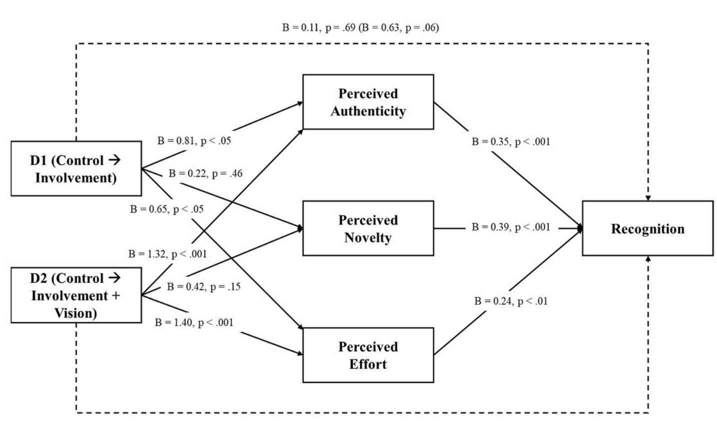
Fig. 2. Results from experiment 2: The effects of involvement and vision on the evaluation of art co-created with AI.

artness (D1: B = 0.56, 95% CI = [0.10, 1.12]; D2: B = 0.92, 95% CI = [0.42, 1.52]) and liking (D1: B = 0.48, 95% CI = [0.08, 1.00]; D2: B = 0.78, 95% CI = [0.33, 1.35]). Besides, the effect of condition on artness is also transmitted by effort for both dummies (D1: B = 0.44, 95% CI = [0.04, 0.93]; D2: B = 0.95, 95% CI = [0.38, 1.66]) and by effort on recognition for D2: B = 0.33, 95% CI = [0.05, 0.68]; see Figs. 3 and 4.

3.6. Discussion

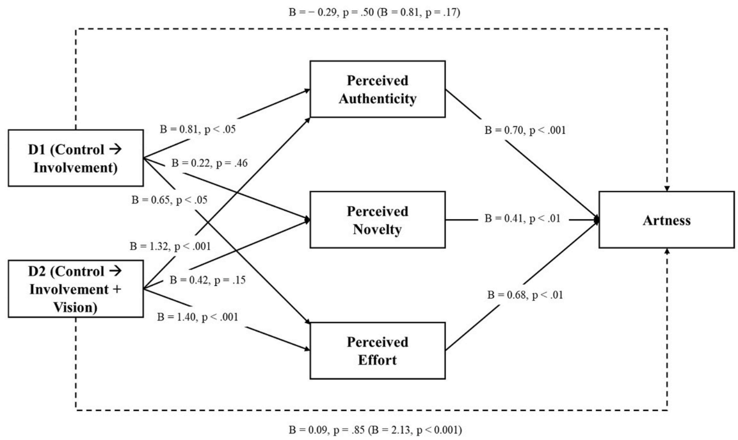
The aim of Experiment 2 was to understand how artists can increase authenticity when co-creating with artificial intelligence. In line with the expectations, signaling human involvement by training the AI tool with a curated set of images by the artist increases recognition of the artwork compared to a control condition using a simple off-the-shelf tool. Furthermore, the results show that this effect is primarily driven by the perception of greater authenticity. The findings also show that adding a vision to the control condition further enhances these effects.

In the previous studies I have assumed that the painter intends to create art. However, many professions in the creative sector create products, such as illustrations or stock images, that are not considered art in the conventional sense. While art is concerned with human expression and the communication of an idea for its own sake (Hagtvedt & Patrick, 2008), especially not with the primary aim of commercial gain, craft is designed for a specific purpose, often motivated by economic or other extrinsic factors (Jindal et al., 2016). Another distinction is between ’high’ and ’low’ art, based on art literature and sociological research on what constitutes legitimate art. High art is intended to engage audiences intellectually, represents ’art for art’s sake,’ and meets sophisticated upper-class standards, while low art is made to be aesthetically appreciated, serve a specific purpose, and appeals to the masses (Bourdieu, 1984; Fisher, 2013, p. 477). In evaluating what is authentic, audiences will examine the intent of the creator and the creative control exercised over the process (Kreuzbauer & Keller, 2017; Valsesia et al., 2016). Creative control is a means of ensuring that the final product adheres to the creator’s vision, which is even more important when creating a work of art as opposed to an art-like product (Kreuzbauer et al., 2015; Valsesia et al., 2016). Thus, I hypothesize that commercial (vs. non-commercial) motivations directly influence authenticity and interact with the use of generative AI in such a way that the use of tools (which reduces creative control) is less acceptable and leads to lower levels of inferred authenticity when the goal is to create art than when the goal is to create a non-art product (see, e.g., Bhattacharjee et al., 2014; Jung et al., 2023; Wang et al., 2023; Verhaal & Dobrev, 2022).



Note: Values in parentheses indicate the effect of condition on recognition when the mediators (i.e., authenticity, novelty, and effort) are not included.

Fig. 3. Results of mediation analysis in Experiment 2: Involvement and vision affect recognition via authenticity.



Note: Values in parentheses indicate the effect of condition on artness when the mediators (i.e., authenticity, novelty, and effort) are not included.

Fig. 4. Results of mediation analysis in Experiment 2: Involvement and vision affect artness via authenticity.

4. Experiment 3: art versus non-art

4.1. Participants

One hundred sixty participants completed the study on Prolific Academic in exchange for an average of 1.20 $. Inclusion criteria was completion of at least 10 previous studies. One participant was excluded from further analysis because he indicated that he had not paid attention, leading to a final sample size of one hundred and fifty-nine participants (39 female, 118 male, two declined to respond; age: $M = 31.55$, $SD = 9.40$, $Min = 18$, $Max = 72$).

4.2. Procedure

This experiment used a 2 (stated intention: art vs. non-art) × 2 (execution: human vs. collaboration) between participants design. Participants in all conditions were shown a collection of paintings by an artist. In the art condition, they read that the artist intended to create art that would convey the painter's inner feelings, while in the non-art condition, they read that the images were intended to be sold on stock image platforms for profit. In the human execution condition, participants read that the entire creative process was controlled by the artist, while in the collaboration condition they learned that the artist was assisted by a generative AI at various stages of the creative process and were shown a sample description of an AI tool (see Appendix 6 for full stimuli; images were generated using Adobe Firefly).

Participants in all conditions were then asked to indicate perceptions of the collection's authenticity, novelty, and effort, as well as artness and recognition using the same scales as in Experiment 1. For liking the scale was extended by three additional items adapted from Yalcin et al. (2022). Psychometric properties of the scales were tested using a confirmatory factor analysis (CFA, estimator MLR in the R-library lavaan [Rosseel, 2012]), which showed acceptable model fit (Chi-squared $= 254.117$, $df = 105$, $CFI = 0.909$, $TLI = 0.882$, $RMSEA = 0.095$, $SRMR = 0.056$). Following Fornell and Larcker's (1981) recommended procedure I found no discriminant validity concerns (see Appendix 3 for items).

4.3. Manipulation checks

To test the success of the manipulations participants were asked to answer two questions: "The artist is motivated by" (1 = extrinsic motives, 10 = intrinsic motives; adapted from Van Boven et al., 2010) and "What percentage of the process of creating the paintings is controlled by the artist?" (1 = 0%, 10 = 100%). The result of two independent samples t-tests show that the manipulations were successful: participants in the art condition, relative to those in the non-art condition, reported higher intrinsic motives ($M_{art} = 6.65$, $SD = 2.12$ vs. $M_{non\text{-}art} = 4.74$, $SD = 2.45$, $t(157) = 5.26$, $p < .001$). Similarly, participants in the human condition, relative to the collaboration condition, reported higher levels of creative control ($M_{human} = 9.35$, $SD = 1.57$ vs. $M_{collaboration} = 5.77$, $SD = 2.17$, $t(157) = -11.89$, $p < .001$).

4.4. Main and interaction effects on outcomes and mediators

I conducted a set of 2 (stated intention) × 2 (execution) analyses of variance (ANOVAs) to analyze participants' evaluations of the collection, finding main effects for intention on authenticity and recognition, main effects of execution on all constructs and, as expected, I find interaction effects on authenticity and effort as well as on recognition and artness. The effect of execution was stronger in the art condition compared to the non-art condition (see Fig. 5 and Table 3).

4.5. Moderated mediation analyses

Recognition. In the next step, I analyzed the indirect effect of intention by execution on recognition, mediated by authenticity, novelty, and effort using PROCESS model 7 (10,000 bootstrapped samples; Hayes, 2017), which tests for moderated mediation. Execution was the independent variable (−1 = human, 1 = collaboration), intention (−1 = art, 1 = non-art) was the moderator, and authenticity, novelty, and effort were the mediators. As predicted, I found a significant moderated mediation effect for authenticity (index of moderated mediation: $B = 0.29$, 95% CI = [0.09, 0.53]), and for effort (index of moderated mediation: $B = 0.13$, 95% CI = [0.01, 0.30]). When artists intended to create stock images the effect of collaborating with AI on recognition via authenticity was weaker ($B = -0.30$, 95% CI = [−0.48, −0.14]) than when they intended to create art for a museum ($B = -0.58$, 95% CI = [−0.86, −0.36]). The same pattern was found for the moderated mediation via effort. When artists intended to create stock images, the effect on recognition via effort was weaker ($B = -0.21$, 95% CI = [−0.37, −0.07]) than when they intended to create art ($B = -0.34$, 95% CI = [−0.57, −0.11]).

Liking. Another moderated mediation analysis was used to analyze the effects on liking (model 7; 10,000 bootstrapped samples; Hayes, 2017). The pattern of results was similar and shows a significant moderated mediation effect for authenticity (index of moderated mediation: $B = 0.31$, 95% CI = [0.10, 0.59]), and for effort (index of moderated mediation: $B = 0.15$, 95% CI = [0.01, 0.34]), but not for novelty. The intention to create art (vs. non-art) moderates the effect of

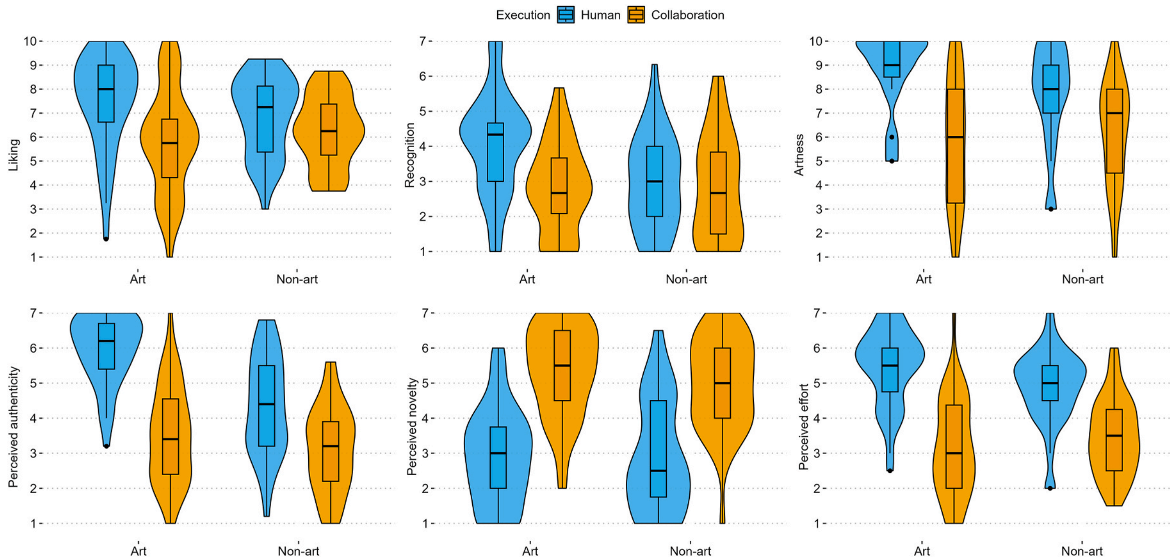


Fig. 5. Main and interaction effects Experiment 3: Collaborating with AI to produce art versus art-like products.

Table 3
Main and interaction effects Experiment 3.

Mediators				
Intention	Execution	Authenticity	Novelty	Effort
Art	Human	5.95 (0.98)	2.88 (1.35)	5.45 (1.09)
Art	Collaboration	3.53 (1.36)	5.34 (1.29)	3.17 (1.38)
Non-art	Human	4.34 (1.40)	2.90 (1.58)	4.87 (1.06)
Non-art	Collaboration	3.12 (1.20)	4.96 (1.32)	3.45 (1.08)
Intention		*F(1,155) = 23.49, p < .001*	F (1,155) = 1.10, p = .30	F (1,155) = 0.32, p = .57
Execution		*F(1,155) = 85.37, p < .001*	*F(1,155) = 105.46, p < .001*	*F(1,155) = 101.24, p < .001*
Interaction		*F(1,155) = 9.16, p < .01*	F (1,155) = 0.81, p = .37	*F(1,155) = 5.40, p < .05*
Outcomes				
Intention	Execution	Recognition	Liking (10-point)	Artness (10-point)
Art	Human	4.09 (1.46)	7.46 (1.97)	8.85 (1.60)
Art	Collaboration	2.83 (1.27)	5.83 (2.17)	5.79 (2.64)
Non-art	Human	2.97 (1.34)	6.88 (1.63)	7.69 (2.12)
Non-art	Collaboration	2.82 (1.47)	6.23 (1.47)	6.10 (2.20)
Intention		*F(1,155) = 5.99, p < .05*	F (1,155) = 0.04, p = .85	F (1,155) = 1.10, p = .30
Execution		*F(1,155) = 10.49, p < .01*	*F(1,155) = 15.63, p < .001*	*F(1,155) = 45.74, p < .001*
Interaction		*F(1,155) = 6.22, p < .05*	F (1,155) = 2.82, p = .09	*F(1,155) = 4.52, p < .05*

execution via authenticity and effort on liking.

Artness. To analyze the effects on perceptions of artness I conducted another moderated mediation analysis (model 7; 10,000 bootstrapped samples; Hayes, 2017). Again, I find the same pattern of results: The intention to create art (vs. non-art) moderates the effect of execution via authenticity and effort on artness: index of moderated mediation for authenticity: B = 0.36, 95% CI = [0.12, 0.68] and index of moderated mediation for effort: B = 0.31, 95% CI = [0.05, 0.62].

4.6. *Discussion*

Experiment 3 demonstrates that the impact of using AI during the creative process is more pronounced when the artist intends to create art as compared to art-like artifacts, such as illustrations.

5. General discussion

Understanding how audiences react to art co-created with generative AI and artists who use AI, is important both theoretically and from a practical perspective. To address these questions, I conducted three empirical studies. Experiment 1 shows that when viewers are informed that a visual artwork was created with the assistance of AI, they tend to evaluate it less favorably (resulting in lower levels of recognition, aesthetic appreciation, and perceptions of artistic value) – even when the artifact is objectively identical. The observed effects are driven by three pathways: Viewers perceive art co-created with AI as less authentic and requiring less effort. On the positive side, however, co-created art is perceived as more novel. Using AI during ideation (i.e., brainstorming ideas with a chatbot) has a less negative impact on evaluation than using AI during implementation (i.e., generating layouts with text-to-image AI). Viewers find works of art to be most inauthentic when an original idea of the artist was implemented with the help of AI or when both, idea and implementation were assisted by AI. In addition, this research reveals that the use of AI influences how artists are perceived. Artists who collaborate with AI and disclose it receive lower levels of admiration. This outcome is driven by two competing pathways: Less artistic authenticity but increased creativity.

The second experiment focuses on the implementation stage of the creative process and illustrates how revealing human input during co-creation with AI (i.e., by guiding the tool with a curated training data-set) can restore authenticity and improve the evaluation of the resulting artwork. I compare the use of an off-the-shelf product (such as Mid-journey) to the use of an algorithm trained by the artist with a condition that adds a vision for the use of AI. Revealing the artist's reason for using AI and communicating a vision (e.g., to see nature through the eyes of the machine) is perceived by viewers as even more authentic.

Finally, experiment 3 confirms the interaction between the use of AI and stated motives. The evaluation of AI use depends on the motives of the painter. Those who create illustrations and stock images (produce art-like craft or low art) suffer less from the use of AI during creation than those who intend to create high art. Creative control and intentions interact to influence the evaluation of the product through authenticity and perceived effort.

The collected evidence reveals that the way and timing of using AI in art-making impacts the perception of the created artwork and the artist. Audiences have different criteria for evaluating art compared to art-like items such as illustrations, and they are more accepting of AI use for the second category. These findings have important theoretical and practical implications.

5.1. Theoretical implications

From a theoretical perspective this research contributes to four literature streams: algorithm aversion, human-AI-collaboration, authenticity, and human branding. Beyond delineating the effects of AI infusion into the creative process on recognition, liking, and perceptions of artness, this research sheds light on the processes that connect co-creation with AI and art evaluation: authenticity, effort, and novelty, thereby providing a richer understanding of the mechanisms. These findings are relevant from the broader perspective of algorithm aversion (Dietvorst et al., 2014; Castelo et al., 2019; for a review see: Mahmud et al., 2022). Artistic creation is a deeply subjective, intuitive, and symbolic process that involves intentions and emotions and is associated with the meaning of being human (Castelo et al., 2019; Granulo et al., 2021; Millet et al., 2023). According to Castelo et al. (2019), creative tasks like composing music or writing are particularly susceptible to algorithmic aversion. The current study supports and extends this prior research which suggests that the use of AI in art creation would be met with negative reactions and shows that infusing AI in creative processes reduces evaluation of the final product and the artist and uncovers the mechanisms that transmit these effects.

With respect to human-AI-collaboration this research is new in that it investigates how partnership with AI during the creative process is perceived, rather than investigating how the automation of art creation is perceived (see, for example, Chamberlain et al., 2018; Millet et al., 2023; Samo & Highhouse, 2023) or how human intervention in the selection of high-quality AI artwork is perceived (human-in-the-loop; see Köbis & Mossink, 2021; Gunser et al., 2022; Hitsuwari et al., 2023). Interestingly, the generation of ideas through AI-powered text-to-text models, such as chatbots, does not have a negative impact on the assessment of artwork. However, the appeal of the artwork's aesthetics is reduced, particularly when the idea originated from the artist but was implemented using AI. Overall, the findings show that using AI to create art does not diminish the value of the final product, as long as the layout and design are not machine-generated with a simple off-the-shelf product that requires nothing more than a prompt to generate the outcome.

This work also reinforces previous findings that authenticity is a central construct in the valuation of cultural products (Kreuzbauer & Keller, 2017). The literature propagates two determinants that audiences use to infer whether a product is authentic: intention of the producer (e.g., Bhattacharjee et al., 2014; Jung et al., 2023; Moulard et al., 2014, 2015; Verhaal & Dobrev, 2022; Wang et al., 2023) and creative control over the process (Kreuzbauer et al., 2015; Valsesia et al., 2016). While there is much research on the role of intentions on perceptions of authenticity, there is much less research on creative control and the interaction between the two. In this research, I primarily conceptualize the use of generative AI within the creative process as a way to reduce creative control. However, an additional analysis of the data from experiment 3 shows that AI use in the creation process also impacts inferred motives and that the effect of AI use on authenticity runs via both mechanisms although significantly stronger via the creative control route (see additional analysis in the appendix). I suggest that the use of AI at different stages affects authenticity for different reasons. Collaboration during implementation may reduce creative control, which reduces the clarity of the artist's vision (see Valsesia et al., 2016). This is consistent with the data from experiment 1: submitting an original idea to AI implementation reduces authenticity more than painting an idea brainstormed with AI. Using a chatbot for idea generation gives the impression that an artwork is not an honest representation of the artist's inner feelings or biography (see Fine, 2003) and that external incentives are being pursued in favor of integrity and passion (Beverland et al., 2008; Bhattacharjee et al., 2014). In experiment 3, I find that reception of AI use depends on the stated intention of the artist pointing to an interaction between creative control and motivations. Future research might want to build upon these finding and investigate boundary conditions for the effects of AI infusion into the creative process and how other technological tools such as Photoshop may impact the perceived authenticity of artworks.

Finally, this research also contributes to our understanding of how people perceive artists and adds to the body of literature on human brands (e.g., Moulard et al., 2014, 2015; Thomson, 2006). As generative AI advances, it becomes increasingly important to understand how credit for art production and artist involvement is perceived (Epstein et al., 2020). The results demonstrate that the use of tools in an artist's work process is linked to the emotions people experience towards the artist. In the field of art creation, people are often respected based on their ability to attain outstanding results. Nevertheless, I am not aware of any studies investigating admiration for artists, especially in the context of manipulating work processes and measuring emotional responses to the target. This study shows that people show less admiration for those who create using AI tools compared to those who follow traditional creation processes. Such traditional processes are often characterized by manual labor, which provides benefits for the evaluation of the final product, such as the perception that the product contains 'love' (Fuchs et al., 2015). I show that admiration is contingent on perceived authenticity and creativity. Viewers penalize those artists whom they do not find authentic (e.g., because they assume they are driven by the wrong motives; see Bhattacharjee et al., 2014; Moulard et al., 2014), and praise those whom they find innovative and creative.

5.2. Practical implications

The results of this research have important implications for the creative professions. As generative AI advances and more ('specialized') tools become available, artists face the choice of using them to their advantage or staying away from them. However, artists are well advised to be careful when using AI, as its use may signal inauthenticity and is detrimental to the perception of the artwork and the artist, especially when using off-the-shelf tools. One way therefore is the conscious use of AI tools, which attempts to harness the benefits of AI (e.g., perceived novelty) without sacrificing authenticity. This path requires artists to signal creative control and integrity during the creation process by a) revealing human labor and b) by communicating intentions and why AI can help achieve the artist's vision. A good example is Ambrosi, who uses DeepDream to augment landscape images. He preserves authenticity by explaining his vision and why the use of AI can help him achieve it. He submits his original work (a landscape photography) to a customized algorithm, which he manipulates until the result matches his vision, thereby signaling creative control over the process. When disclosing the use of AI in the creation of artworks, it may be beneficial to highlight the amount of involvement from the artist. For instance, artists could expose the hidden labor behind the training of a customized algorithm by displaying the dataset (Hemment et al., 2023). Using algorithms specifically trained for an artist's purpose (rather than off-the-shelf solutions where a simple prompt is all that is required), and using training data from the artist's own collection, can be a way to increase authenticity through creative control. In this way, the artist owns the tool and the creative process embraces the tool. Artist David Young already uses this strategy when he feeds his own image collections into a customized GAN and observes the learning process. He co-creates new compositions that reflect the machine's interpretation of the subject. Finally, he selects images and paints them with oil (www.davidyoung.art). However, artists should not rely too much on the novelty effect, as novelty diminishes as more and more artists rely on generative models.

This research suggests that creators' use of AI is sanctioned differently by audiences depending on whether they produce high art or low art. Audiences are more forgiving when an illustrator uses generative AI than when an artist does. This may seem like a positive development for illustrators, but in the end, these professions may be the most at risk of being displaced by generative AI, which can create thousands of illustrations in a matter of seconds (Smith et al., 2023). As historical examples show, new technologies change the activities of professions; for example, the advent of photography freed artists from commercial portrait painting. So, there is a constant need to adapt to new developments, and the rise of generative AI may mean that artists will have to deliberately rely on traditional, artisanal processes to differentiate themselves from low art producers.

Finally, while some artists will voluntarily reveal AI in their creative process and its use to recipients in the hope of positive effects (e.g. novelty), others may fear negative evaluations. Even though art may not require regulations as strict as journalism (Stark & Diakopoulos, 2016) or science where many academic journals now require disclosure of the involvement of AI tools (e.g. Nature, PNAS; Brainard, 2023), the transparency of algorithmic presence is still a matter of fairness and accountability.

5.3. Avenues for further research

I studied the work of art and how artists and their artifacts might be affected by the use of AI in the creative process. Future studies could investigate the impact of AI involvement in art production on perceptions of luxury. Traditional production processes involving manual labor have been shown to be preferred in certain contexts, such as when the product is intended as a gift for close others (Fuchs et al., 2015). AI augmentation may be acceptable for commodity art that is inexpensive, but may be unacceptable for fine art.

How people experience and evaluate art might depend on their art interest and expertise (Specker et al., 2020). A reanalysis of Experiment 1, which considered participants' interest in art, found no effect of interest in art on evaluation of artworks (see Appendix 8), but perceptions may differ between experts and laypeople. Future studies could validate these findings by using samples of art-literate participants, such as art students.

The implications of this study are also expected to change due to technological advances. The extensive use of AI in the creative domain can lower the perceived novelty of creating with AI. Therefore, further research or longitudinal studies may be warranted to see how the appreciation of the use of AI in art changes.

Declarations of interest

None.

CRediT authorship contribution statement

Uwe Messer: Conceptualization, Methodology, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

There are no competing interests to declare.

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Appendix 1. Constructs and measures Experiment 1

Table 2
Constructs and measures Experiment 1.

Construct and Source	Item	Scale	Factor Loading	AVE	CR	α
Manipulation Check 1	The artist used "Create" to find the idea for the painting.	1	–	–	–	–
Manipulation Check 2	The artist used "Implema" to generate different layouts for the painting.	1	–	–	–	–
Recognition (Valsesia et al., 2016)	Being recognized in an annual competition as best in category.	1	0.73	0.49	0.74	0.75
	Being recognized in 10 years as having impacted the tradition of art.		0.74			
	Being included in a time capsule to be opened in 100 years.		0.63			
Aesthetic Liking	From an aesthetic point of view, I find this picture …	2	–	–	–	–
Artness	Do you think this picture is art?	3	–	–	–	–
Creative Authenticity (Valsesia et al., 2016)	This painting …	1		0.74	0.93	0.93
	is a result of what the artist really thinks and feels.		0.82			
	is an expression of the artist's personality.		0.83			
	reflects true inspiration.		0.88			
	is an honest work.		0.88			
	is authentic.		0.89			
Novelty (inspired by Moldovan et al., 2011)	The creation process is unusual.	1	0.72	0.64	0.78	0.77
	The creation process is novel.		0.86			
Effort (Kruger et al., 2004)	How much effort did the artist put into the painting?	4	0.98	0.83	0.90	0.89
	How long do you think it took to paint the picture?	5	0.82			
Admiration (Fiske & Dupree, 2014; Sweetman et al., 2013)	To what extent do you feel the following for the artist?	1		0.78	0.92	0.91
	Admiration		0.84			
	Respect		0.91			
	Appreciation		0.90			
Artist Authenticity (Moulard et al., 2014)	This artist has a real passion for her art.	1	0.95	0.86	0.95	0.95
	This artist shows a strong dedication to her paintings.		0.95			
	Committed is a word I would use to describe this artist.		0.89			
Artist Creativity (inspired by Katz et al., 2022)	This artist is very innovative.	1	0.87	0.71	0.88	0.88
	This artist is ahead of the times.		0.84			
	This artist is an innovative thinker.		0.83			
Scales						
1	1 = "not at all" to 7 = "very much"					

(*continued on next page*)

Table 2 (*continued*)

Construct and Source	Item	Scale	Factor Loading	AVE	CR	α
2	1 = “not aesthetically pleasing at all” to 10 = “very aesthetically pleasing”					
3	1 = “definitely not art” to 10 = “definitely art”					
4	1 = “not much effort” to 7 = “very much effort”					
5	1 = “very short time” to 7 = “very long time”					

Appendix 2. Constructs and measures Experiment 2

Table 4
Constructs and measures Experiment 2.

Construct and Source	Item	Scale	Factor Loading	AVE	CR	α
Recognition (Valsesia et al., 2016)	Being recognized in an annual competition as best in category.	1	0.78	0.56	0.79	0.77
	Being recognized in 10 years as having impacted the tradition of art.		0.86			
	Being included in a time capsule to be opened in 100 years.		0.59			
Aesthetic Liking	From an aesthetic point of view, I find this picture …	2	–	–	–	–
Artness	Do you think this picture is art?	3	–	–	–	–
Creative Authenticity (Valsesia et al., 2016)	This painting …	1		0.70	0.91	0.92
	is a result of what the artist really thinks and feels.		0.78			
	is an expression of the artist’s personality.		0.81			
	reflects true inspiration.		0.82			
	is an honest work.		0.88			
	is authentic.		0.87			
Novelty (inspired by Moldovan et al., 2011)	The creation process is novel.	1	–	–	–	–
Effort (Kruger et al., 2004)	How much effort did the artist put into the painting?	4	0.90	0.71	0.83	0.82
	How long do you think it took to paint the picture?	5	0.77			
Scales						
1	1 = “not at all” to 7 = “very much”					
2	1 = “not aesthetically pleasing at all” to 10 = “very aesthetically pleasing”					
3	1 = “definitely not art” to 10 = “definitely art”					
4	1 = “not much effort” to 7 = “very much effort”					
5	1 = “very short time” to 7 = “very long time”					

Appendix 3. Constructs and measures Experiment 3

Table 5
Constructs and measures Experiment 3.

Construct and Source	Item	Scale	Factor Loading	AVE	CR	α
Recognition (Valsesia et al., 2016)	Being recognized in an annual competition as best in category.	1	0.90	0.57	0.78	0.81
	Being recognized in 10 years as having impacted the tradition of art.		0.70			
	Being included in a time capsule to be opened in 100 years.		0.66			
Liking (Yalcin et al., 2022)	Very bad - very good	–	0.74	0.72	0.92	0.91
	Very negative - very positive		0.96			
	Not at all favorable - very favorable		0.67			
	Not aesthetically pleasing at all – very aesthetically pleasing		0.85			
Artness	Do you think this picture is art?	3	–	–	–	–
Creative Authenticity (Valsesia et al., 2016)	This collection …	1		0.73	0.93	0.93
	is a result of what the artist really thinks and feels.		0.81			
	is an expression of the artist’s personality.		0.82			
	reflects true inspiration.		0.91			
	is an honest work.		0.84			
	is authentic.		0.89			
Novelty (inspired by Moldovan et al., 2011)	The creation process is novel.	1	0.84	0.70	0.82	0.82
	The creation process is unusual.		0.83			
Effort (Kruger et al., 2004)	How much effort did the artist put into the collection?	4	0.93	0.84	0.91	0.91
	How long do you think it took to paint the collection?	5	0.90			
Scales						
1	1 = “not at all” to 7 = “very much”					
3	1 = “definitely not art” to 10 = “definitely art”					
4	1 = “not much effort” to 7 = “very much effort”					
5	1 = “very short time” to 7 = “very long time”					

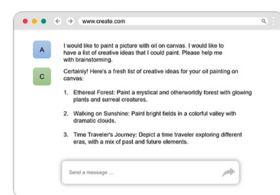
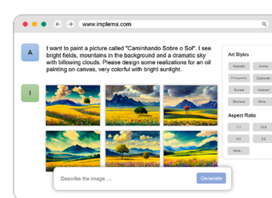
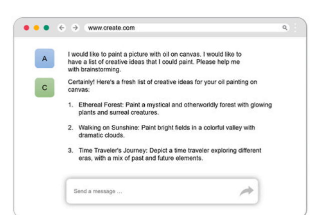
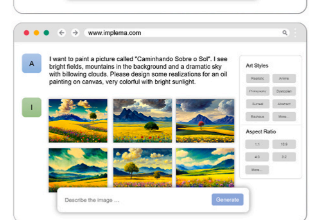
APPENDIX

Appendix 4. Stimuli Experiment 1

The following picture was shown to all participants.

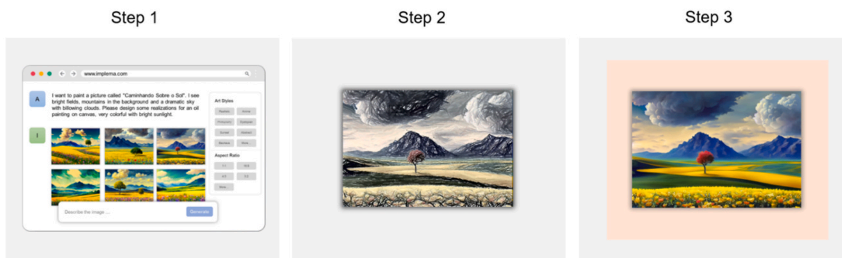
Image source: https://pixabay.com/illustrations/impressionism-wildflowers-7382951/

Stimuli by condition

Ideation	Implementation	Text	Interface shown to participants
Artist	Artist	Artist: In the beginning I delved into myself to find a first idea for the painting. In this process, several potential ideas emerged and I decided on “Caminhando Sobre o Sol” (Walking on Sunshine). In the next step I used my imagination to develop a realization for the idea. I experimented with several image compositions, which I finally combined and painted with oil on canvas.	none
AI	Artist	Artist: In the beginning, I used Create (note: a chatbot based on artificial intelligence) to brainstorm an initial idea for the painting. In this process, several potential ideas emerged and I decided on “Caminhando Sobre o Sol” (Walking on Sunshine). In the next step I used my imagination to develop a realization for the idea. I experimented with several image compositions, which I finally combined and painted with oil on canvas. Below you see the interface of the tool.	
Artist	AI	Artist: In the beginning I delved into myself to find a first idea for the painting. In this process, several potential ideas emerged and I decided on “Caminhando Sobre o Sol” (Walking on Sunshine). In the next step I used Implema (note: an artificial intelligence-based application that generates images) to develop a realization for the idea. Implema produced several image compositions, which I combined and finally painted with oil on canvas. Below you see the interface of the tool.	
AI	AI	Artist: In the beginning, I used Create (note: a chatbot based on artificial intelligence) to brainstorm an initial idea for the painting. In this process, several potential ideas emerged and I decided on “Caminhando Sobre o Sol” (Walking on Sunshine). In the next step I used Implema (note: an artificial intelligence-based application that generates images) to develop a realization for the idea. Implema produced several image compositions, which I combined and finally painted with oil on canvas. Below you see the interfaces of the tools.	 

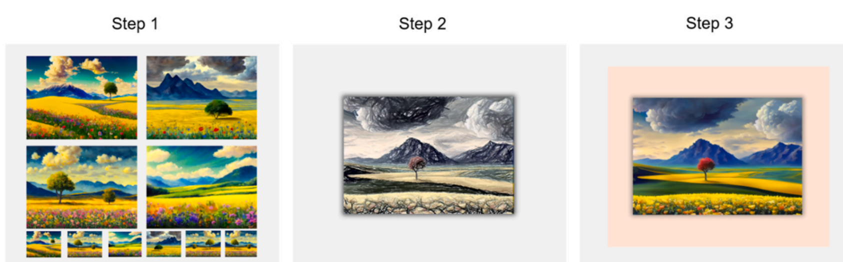
Appendix 5. Stimuli Experiment 2

Control.



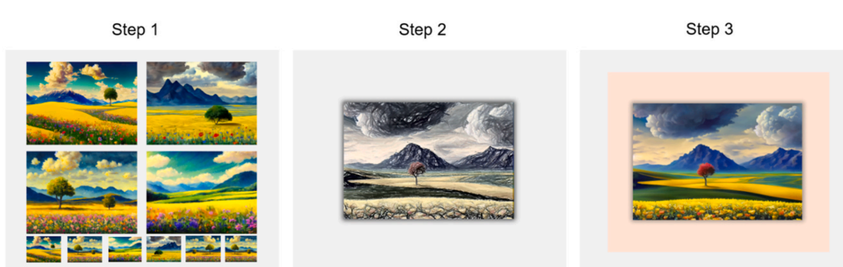
The work with the title "Walking on Sunshine" is based on an AI technology known as Generative Adversarial Networks (GANs). Initially, the artist used an AI tool that had already been trained by the developer on a very large number of images from the Internet. Using text input, the artist described what the image should look like (step 1). The AI then began to generate new landscape images based on this description (step 2). In the final step (3), a generated image (center) was used as a source for the human painter. The result is a human-generated oil painting (right) based on a machine-generated image.

Involvement.



The work with the title "Walking on Sunshine" is based on an AI technology known as Generative Adversarial Networks (GANs). First, the artist trained the AI with a large number of his own landscape paintings, which he had painted over several years (step 1). The AI then began to generate new landscape images based on these images (step 2). In the final step (3), a generated image (center) was used as a source for the human painter. The result is a human-generated oil painting (right) based on a machine-generated image.

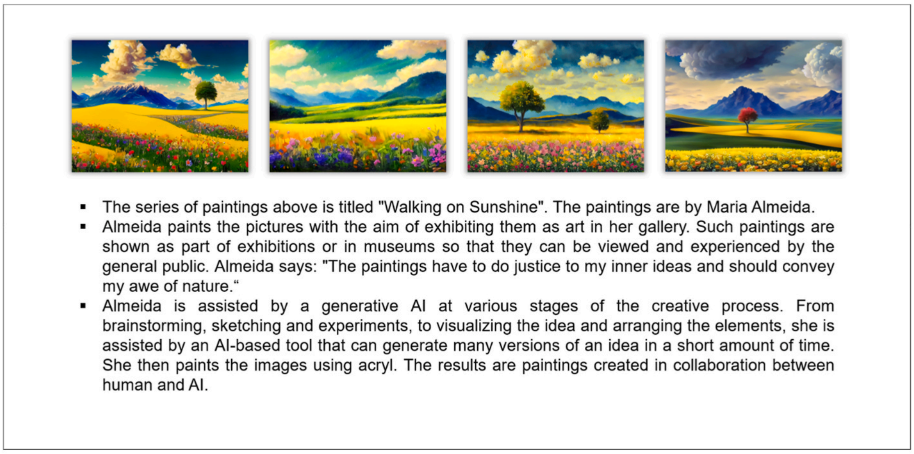
Involvement and Vision.

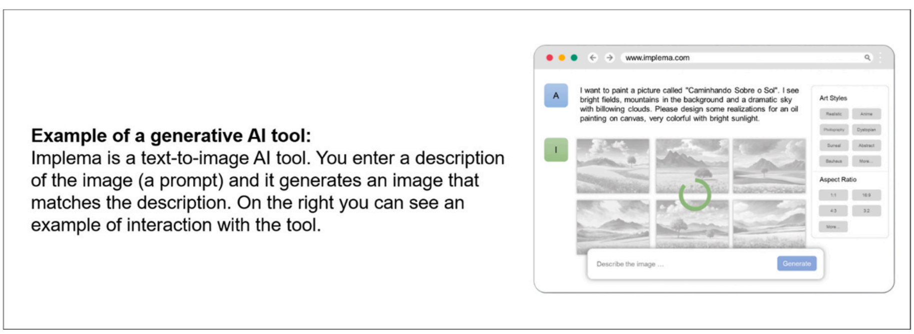


The work with the title "Walking on Sunshine" is based on an AI technology known as Generative Adversarial Networks (GANs). First, the artist trained the AI with a large number of his own landscape paintings, which he had painted over several years (step 1). His aim is to understand how AI interprets nature in his images. He is interested in understanding the relationship with nature in a new way, seeing through the eyes of the machine and adding the new perspective to the human perspective. The AI then began to generate new landscape images based on these images (step 2). In the final step (3), a generated image (center) was used as a source for the human painter. The result is a human-generated oil painting (right) based on a machine-generated image.

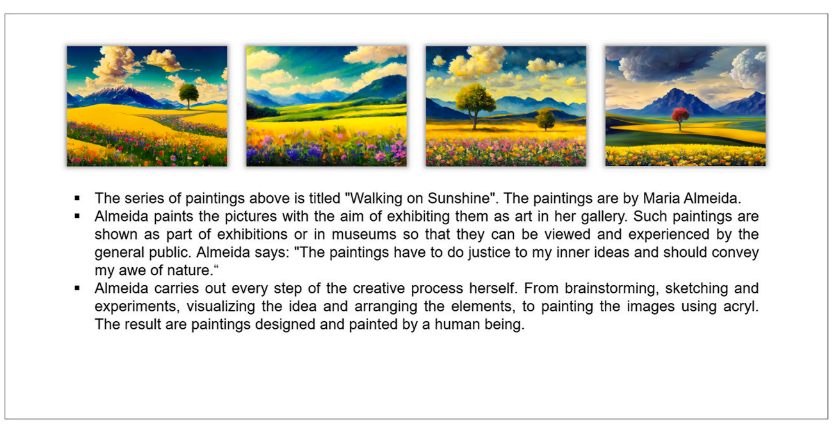
Appendix 6. Stimuli Experiment 3

Art/low control.

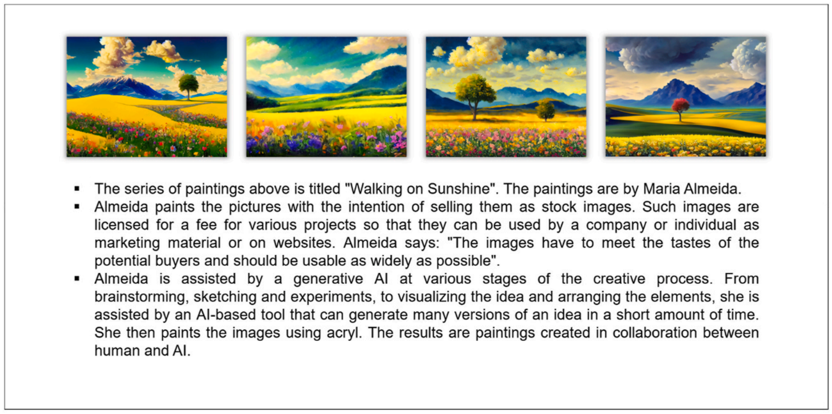


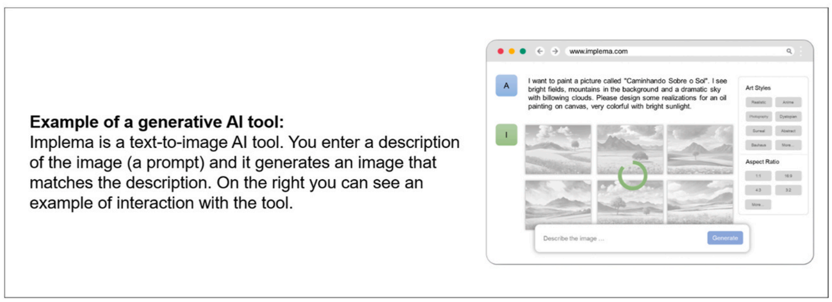


Art/high control.

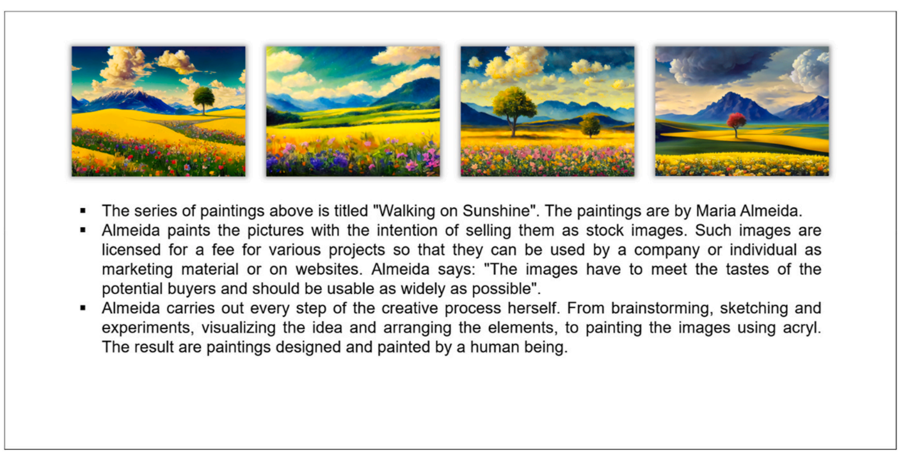


Stock image/low control.





Stock image/high control.



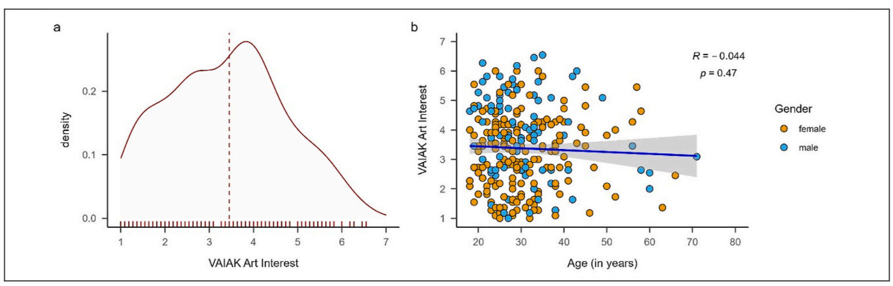
Appendix 7. Additional analysis of Experiment 3 as reported in the discussion

I re-analyzed the data of experiment 3 to investigate whether use of AI in the creative process affects authenticity via creative control and inferred motives using a parallel mediation analysis (PROCESS model 4, 10,000 bootstrapped samples; Hayes, 2017). I measured the mediators using the manipulation checks from experiment 3 (creative control: "What percentage of the process of creating the paintings is controlled by the artist?", 1 = 0%, 10 = 100%; inferred motives: "The artist is motivated by 1 = extrinsic motives, 10 = intrinsic motives). Execution was the independent variable (-1 = human, 1 = collaboration), authenticity was the dependent variable, creative control and inferred motives were the mediators, and intention (-1 = art, 1 = non-art) was included as a covariate. I find an effect of execution on creative control ($B = -1.79$, 95% CI = [-2.09, -1.49]) and inferred motives ($B = -0.74$, 95% CI = [-1.09, -0.40]). Further, I find effects of the mediators on authenticity (creative control: $B = 0.26$, 95% CI = [0.17, 0.35]; inferred motives: $B = 0.21$, 95% CI = [0.14, 0.29]). The indirect effect of execution on authenticity through inferred motives was significant (indirect effect: $B = -0.16$, 95% CI = [-0.27, -0.07]), even while controlling for the alternative mediator. The indirect effect of execution on authenticity via creative control was, as already known, significant, too (indirect effect: $B = -0.47$, 95% CI = [-0.68, -0.27]). To test the relative indirect effect size of creative control versus inferred motives in the parallel mediation model, I conducted a pairwise comparison using the "contrast" command in PROCESS (Hayes, 2017). When the indirect effects of creative control versus inferred motives were directly contrasted, creative control mediated to a significantly greater degree (contrast: B = 0.31, 95% CI = [0.08, 0.55]).

Appendix 8. Robustness tests of Experiment 1 as reported in the discussion

To further assess the stability of the findings from Experiment 1 I conducted robustness tests. In Experiment 1 art interest was captured using the 11-item art interest subscale of the VAIAK scale (Vienna Art Interest and Art Knowledge Scale; Specker et al., 2020; sample item: "During my everyday life I spontaneously notice art objects that I find fascinating"; measured on a 7-point Likert scale). VAIAK art interest measures "[…] the amount of time and money spent on art-related behaviors [which] represents the amount of interaction with art" (Specker et al., 2020, p. 173). A CFA on the VAIAK scale indicated sufficient construct reliability (α = 0.92, CR = 0.92, AVE = 0.57). Participants in the sample showed average levels of art interest (M = 3.39, SD = 1.33, Median = 3.45, Min = 1, Max = 6.55) and the distribution of the VAIAK score was right skewed. Since art interest could be related to age, I tested the correlation between age and VAIAK art interest, which was not significant ($r = 0.04$, $p > .05$). Next, I reran the ANCOVAs for the dependent variables liking, recognition, and artness with the covariates VAIAK art interest and age. The analyses revealed that the results were very similar in that the effects of ideation and implementation and their interaction did not change in direction or significance, confirming the robustness of the conclusions.

	Recognition	Liking (10-point scale)	Artness (10-point scale)
Ideation	$F(1,272) = 0.25$, $p = .62$	$F(1,272) = 0.13$, $p = .72$	$F(1,272) = 0.74$, $p = .39$
Implementation	$F(1,272) = 10.57$, $p < .01$	$F(1,272) = 14.91$, $p < .001$	$F(1,272) = 42.87$, $p < .001$
Interaction	$F(1,272) = 2.46$, $p = .12$	$F(1,272) = 4.93$, $p < .05$	$F(1,272) = 3.28$, $p = .07$
VAIAK Interest	$F(1,272) = 2.60$, $p = .11$	$F(1,272) = 0.27$, $p = .60$	$F(1,272) = 0.14$, $p = .71$
Age	$F(1,272) = 0.19$, $p = .67$	$F(1,272) = 4.74$, $p < .05$	$F(1,272) = 2.80$, $p = .09$



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