

The Role of AI Attribution Knowledge in the Evaluation of Artwork

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Abstract

Artwork is increasingly being created by machines through algorithms with little or no input from humans. Yet, very little is known about people's attitudes and evaluations of artwork generated by machines. The current study investigates (a) whether individuals are able to accurately differentiate human-made artwork from AI-generated artwork and (b) the role of attribution knowledge (i.e., information about who created the content) in their evaluation and reception of artwork. Data was collected using an Amazon Turk sample from two survey experiments designed on Qualtrics. Findings suggest that individuals are unable to accurately identify AI-generated artwork and they are likely to associate representational art to humans and abstract art to machines. There is also an interaction effect between attribution knowledge and the type of artwork (representational vs. abstract) on purchase intentions and evaluations of artworks.

Keywords

AI artwork, creativity, evaluation of artwork, experiment, artificial intelligence, machine learning

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There is a battle rising between humans and machines. It is already being felt rather ominously in fields such as education, healthcare, finance, banking, retail, and transportation. For instance, self-driving technology is expected to replace close to 3,00,000 trucking jobs in the next two decades (Smith, 2018). According to Google Search Trends, the keyword “AI” has been steadily gaining in popularity over the years and has achieved peak popularity in terms of worldwide search interest as of January 2020. The trends are similar for related terms such as artificial intelligence and machine learning. The use of AI has slowly crept into even creative fields such as advertising and art. It could be argued that creativity is one area that humans currently have some edge over machines. According to Nobel laureate Herbert Simon, “we judge thought [or an idea] to be creative when it produces something that is both novel and interesting and valuable” (Simon, 2001, p. 208). Creativity is how we humans set ourselves apart from machines that largely work on algorithms and patterns. The idea that machines are capable of not just identifying patterns and relationships using large-scale historical data but are also able to think outside these patterns to create unique and original creative content such as artworks is of utmost interest and significance to those of us who study creativity and art.

Creativity is a quintessential human endeavor. The idea of machines producing creative content such as artworks further blurs the line between humans and machines. However, automation of the creative process might not always lead to unique, surprising, and out-of-the-box ideas. In the level of automation made possible by current AI technologies, the creative output produced by machines is highly dependent on the input fed to such platforms in the form of images, text, font, and layout. Such creativity that is limited to and based on *improbable* combinations of familiar ideas is what Boden (1996) calls *improbabilist* creativity. What usually makes creative content great is a second type of creativity that Boden (1996) refers to as *impossibilist* creativity, which “concerns novel ideas that, relative to the pre-existing conventions of the domain, the person could not have had before” (p. 269). It has also been argued that internet and digital technologies such as the ones used to produce automated creative content are not capable of generating the unexpected or serendipitous moments (Erdelez et al., 2018).

Notwithstanding, the limitations of AI-generated creative content, very little is known about individuals’ evaluation and reception of AI-generated artworks. If AI-generated artwork is inevitable, it would be important and relevant to explore how people evaluate such artworks. Do individuals view and evaluate artworks produced using AI technologies any differently from those created by humans? More importantly, are consumers even able to differentiate the two and identify artworks produced using only AI technologies? The current project is designed as a two-study approach to (a) understand whether individuals are able to accurately differentiate artworks created by humans from artworks generated by AI technologies and machines and (b) understand the role of

attribution knowledge (i.e., information about the creators of content) in their evaluation and reception of said artworks. To that end, we begin with a short review of literature on creativity and evaluation of artworks along with the role of humans in the creative process. Reviewing literature on human *versus* AI-generated artwork will give us a better idea of how AI-generated creative content differs from that created by humans, and how individuals' evaluation of the two might differ. Finally, given the newness of AI-generated artwork and studies examining such artwork, we propose research questions based on our literature review instead of stating hypotheses.

Literature Review

Evaluation of Artworks

Recently, there has been a surge in AI-generated artwork (Bidshahri, 2019). These artworks produced by algorithms using machine learning and neural networks are for most part indistinguishable from human-made artworks. For instance, 19-year-old programmer, Robbie Barrat, uses generative adversarial network (called GAN) algorithms where two networks act as both the artist and the judge simultaneously to produce artworks that are indistinguishable from human-made works of art (Chakrabarti & Hardzinski, 2019). Research on AI-generated artwork has just begun to emerge with studies looking at issues relating to copyright (Dee, 2018; Svedman, 2020), authorship (McCormack et al., 2019), and ownership (Eshraghian, 2020) along with perceptions, likeability and acceptability of AI artwork (Ch'ng, 2019; Coleman et al., 2019; Hong & Curran, 2019; Lee et al., 2019; Ragot et al., 2020). Of these, public evaluation of AI-generated artwork is an interesting but an under researched area, perhaps because evaluation of artwork is somewhat challenging given the subjective nature of such evaluations.

Even defining art is a daunting undertaking, but one aspect of what makes something a work of art appears to be the role and involvement of humans in the creation of it. In other words, the dominant traditional belief is that "art is made with your hands." For instance, respondents in a study conducted by Lu et al. (2005, p. 93) felt strongly that "a work of art should be a serious piece made with human hands" and the use of any sort of technology in the creation or manipulation of artwork renders it fake, artificial, lacking in originality, lacking in effort and time spent in creation, and lacking in meaning and value. In addition, a work of art needs to evoke an emotional response or a meaningful encounter as a pre-requisite for the audience to fully appreciate and understand it (Lu et al., 2005). Any lack of such emotional response to an artwork would again make it fake or artificial, and steal away the expressiveness needed for something to be considered a work of art. The negative attitudes found abundantly in the literature toward computer-generated or manipulated

artwork suggest that artwork solely generated by machines or AI would also be equally, if not more, considered fake, artificial, and not valuable.

Chamberlain et al. (2018) examined the extent to which individuals are willing to accept computer art as having the same aesthetic value as human-made art. Estimation of value and aesthetic worth of an artwork includes a number of factors such as originality, aesthetic value (Hong & Curran, 2019), financial value (Newman & Bloom, 2012), amount of time and effort taken to produce the artwork (Kruger et al., 2004), and emotional connection (Lu et al., 2005). Participants in Lu's (2005) study "believed that when an artwork is created by another entity (a computer), instead of by human hands, no human feelings can be expressed" (p. 95). Kirk et al. (2009) found that viewers rated images labeled as being generated in Photoshop as less aesthetically pleasing than those images labeled as taken from an art gallery. It can be argued that AI-generated art by definition lacks the feelings and emotions that only humans can bring to the creative process. However, many computer-generated images and technologies like photography have been known to elicit a wide range of strong emotions in viewers. Therefore, it is the perhaps the knowledge or the bias introduced by the knowledge of machine-generated nature of artwork, which we call attribution knowledge, that influences individuals' attitudes toward it rather than the actual fact of their creation by machines. Indeed, some empirical studies in art have shown that images labelled as photoshopped were rated as of less aesthetic value than images labelled as from an art gallery, even though both images in the study were identical (Kirk et al., 2009). Similarly, Moffat et al. (2006) found that individuals preferred music created by humans as opposed to that created by computers irrespective of how they were labelled. Chamberlain et al. (2018) call this a computer-art bias and suggest that the root of this bias could be due to "high-level cognitive judgment that computer art is less value (explicit prejudice) or inherent visual characteristics of computer-generated art that are disliked (implicit prejudice)" (p. 178). An AI-generated art bias can be tested, if the exact same piece of artwork were to be presented to two different groups—one with a text description informing them that the artwork was created fully and only by a machine and a second with a text description noting that the artwork was created by a human—the differences in measured attitudes, evaluations of the artwork and purchase intentions should explain the role of attribution knowledge in the reception of artwork.

Before we examine the impact of attribution knowledge, we need to better understand individuals' self-evaluations of artwork, which is their own inherent notions or impressions of artworks and their creators. We know that artificial intelligence is very good at detecting art forgeries just by looking at a single brushstroke (Elgammal et al., 2018). And art experts with a trained eye and through the use of stylistic analysis called Morellian analysis are able to distinguish and judge the authenticity of artworks (Van Dantzig et al., 1973). However, not much is known about regular people's abilities to identify and evaluate artwork, much less the ones created entirely using AI technologies.

There have been some studies that examine the effect of contextual or curatorial information (such as historical information about artist and style of artwork) presented with the artwork on individuals' evaluation of them. For instance, changing titles of artworks changed the way individuals described those artworks (Franklin et al., 1993) and individuals rated artworks presented with titles as more "meaningful" and less "abstract" than artwork without titles (Russell & Milne, 1997). Very little is known about how humans can or cannot identify and evaluate artwork in the absence of any contextual or curatorial information, particularly when it comes to artwork created by machines. One study by Chamberlain et al. (2018) suggests that individuals attribute abstract artwork to computers or AI and representational artwork to humans. In order to gain more insight into how humans evaluate artwork created by humans in comparison to computers, let us turn our attention to two significant tests that might inform us more about individuals' evaluations of artwork created by artificial intelligence, Turing Test and Lovelace Test.

British mathematician, Alan Turing, proposed the Turing Test (TT) in his seminal paper 'Computing Machinery and Intelligence' (Turing, 1950). While the test itself has been revised and hotly debated over the last 50 years, the crux of Turing's goal was to find an answer to the question, "can machines communicate in natural language in a manner indistinguishable from that of a human being?" (Saygin et al., 2000). Turing illustrates it through a series of Imitation Games designed to essentially test whether a machine can imitate a human successfully.

Turing was very optimistic about machine learning and the likelihood of machines to succeed in the imitation game: "I believe that in about fifty years' time, it will be possible to program computers with a storage capacity of about 10^9 , to make them play the imitation game so well that an average interrogator will not have more than 70 percent chance of making the right identification after five minutes of questioning" (Turing, 1950, p. 442). Indeed, there are numerous examples since the turn of the century such as computer chess games, IBM Watson, chatbots, and voice-enabled virtual assistants that suggest that we are getting closer to creating machines that might one day pass the Turing Test and fulfill his prophecy. Despite these modest achievements in the field of artificial intelligence, Bringsjord et al. (2003) claim that such "attempts to build computational systems able to pass TT (or at least restrictive versions of this test) have devolved into shallow symbol manipulation designed to, by hook or by crook, trick" (p. 215). A better test is one where an artificial intelligent agent A produces an output O , which the human architect H of the system A cannot account for how A produced O (Bringsjord et al., 2003).

This is called the Lovelace test (LT) named after Ada Lovelace, considered the world's first programmer, who believed that until a machine can produce an idea that it was not designed to create, it cannot be considered intelligent in the same way humans are. Lady Lovelace's argument was that computers cannot create anything original, they merely do what humans order them to do via

programs and code (Bringsjord et al., 2003). Unfortunately, just as the case with machines that cannot pass TT, there is not yet a machine or intelligent agent that could pass LT. Machines, thus far, can only perform tasks that can be algorithmized and turned into code, and certain human functions like creativity and empathy cannot yet be turned into code (Pearson, 2014). AI-generated artwork like the ones created by Robbie Barrat's code do push at the boundaries of the LT test. The question though is are humans intuitive enough to realize and identify such artwork from that created by humans?

Based on the review of limited literature in this area, we ask the following two research questions:

RQ1: Are individuals able to accurately identify artwork created by machines using artificial intelligence?

RQ2: What role does attribution knowledge play in the reception of artwork?

Method—Study I

In order to assess individuals' level of knowledge when it comes to identifying artwork created by AI technologies in comparison to those created by humans, we gathered five different types of artwork from the internet that were produced using AI technologies. We included two additional artworks created by humans to see what individuals' reception of those would be in comparison to the five AI-generated ones. Care was taken to choose artworks that were very similar whether they were of trees and landscapes or abstract in nature. The AI-generated artwork was chosen from Robbie Barrat's collection of paintings created using generative adversarial network (GAN) algorithms. Please see appendix for images of all seven artworks.

All seven images were uploaded to Qualtrics and a short survey was created in which respondents were asked to identify the creators of the artwork—a human or a machine (i.e., artificial intelligence (AI) technologies). Also measured on the survey was individuals' self-reported levels of expertise and knowledge of art in general, and some demographic questions such as age, gender, race and income. All respondents saw all seven of the artworks, which were randomized to reduce error. Participants were recruited from Amazon Turk and paid less than a dollar for each completion. The entire survey took on average less than 3 minutes to complete with a median duration of 90 seconds.

Results of Study I

A total of 211 participants completed the survey. The average age of participants in the sample was 38 years and it ranged from 20 to 89 years. Of the 211

participants, 59% were male and 41% were female; about 77% were White/Caucasian, 6% African American, 5% Hispanic, 7% Asian, 2% Native American and the rest selected Other. Table 1 depicts the percentage of respondents who selected either AI technology or human-made in response to the question—who do you think created the artwork you see above? Artworks 1, 2, 5, 6, and 7 are representational in nature and artworks 3 and 4 are abstract in nature.

Our first research question asks whether individuals are able to accurately identify artwork created by GAN and other such AI technologies. Based on the percentages from our sample, only one artwork out of the five AI-generated artworks was correctly identified by a majority of individuals in our sample (Artwork 4 – 82.5% identified is as AI-generated as opposed to 17.5% who incorrectly identified it as human-made). The rest four were incorrectly identified as created by humans. The two human-made artworks were correctly identified as created by humans with artwork 3 receiving a slightly higher percentage than artwork 2. While we found that individuals in our sample were not able to identify artwork created by AI technologies accurately, the more interesting finding is that their impressions were dependent on the type of artwork as found by Chamberlain et al. (2018). The artwork that was correctly identified as AI-generated was abstract in style and the ones attributed to humans was representational in style. These findings support Chamberlain et al. (2018) results that individuals tend to assume that abstract works are AI-generated. This suggests that in addition to attribution knowledge, a second variable of interest that can potentially impact individuals' evaluation of artworks is the type of artwork.

To summarize, we found two interesting things in our first study: (a) Individuals found it hard to identify AI-generated artwork. Only one out of the five AI-generated artworks was correctly identified by our sample. (b) Artwork that was correctly identified as AI-generated was abstract in nature and the artwork correctly identified as created by humans was

Table 1. AI-Generated or Human-Made Crosstabulation.

Artwork	Created by	% of respondents who thought it was created by AI technology	% of respondents who thought it was created by humans
Artwork 1 (representational)	AI	22.7%	77.3%
Artwork 2 (representational)	Human	16.6%	83.4%
Artwork 3 (abstract)	Human	15.6%	84.4%
Artwork 4 (abstract)	AI	82.5%	17.5%
Artwork 5 (representational)	AI	29.9%	70.1%
Artwork 6 (representational)	AI	36%	64%
Artwork 7 (representational)	AI	47.4%	52.6%

representational in nature as found in previous studies. Combined together, these two findings form the basis and rationale for our second study. In addition to the role of attribution knowledge, based on the findings of our first study, it would be interesting to examine the role of the type of artwork (abstract vs. representational) as a second independent variable in our second study. A modified research question that guides our second study is therefore: What effect does attribution knowledge (i.e., information about the creator of the artwork) have on individuals' evaluation of artwork and how does this knowledge interact with the type of artwork (abstract vs. representational) shown to them?

Method—Study 2

To recap, study 1 found that individuals are not able to distinguish and identify accurately artwork created by AI technologies and there appears to be a relationship between the type of artwork and individuals' evaluation of it. To test the impact of attribution knowledge and the type of artwork on individuals' evaluations, we designed an experiment with four of the artworks that were used in study 1. In choosing the four artworks, we picked two artworks (one created by AI and one by a human) that were identified correctly by majority and two (again, one created by AI and one created by a human) that were identified incorrectly by majority of our sample in study 1. These artworks were two of abstract style and two of representational style. Readers will recall that the respondents in our sample in study 1 attributed both abstract artworks to AI (although only one was created by AI and the other by a human) and both the representational artworks to humans (although only one was created by a human and the other by AI). In other words, the four artworks we selected were not only the ones that our sample in study 1 were most and least likely to associate with humans and AI but they also were of two different types—abstract and representational, creating a second independent variable for our second experiment.

As seen in Table 1, AI-generated artworks 1 (representational) and 4 (abstract) received the least and highest percentages of participants identifying them correctly as machine-made respectively. Unfortunately, we only used two human-made artworks in our first study so there was not a greater variation in their identification percentages so we included both of them (artworks 2 and 3) as stimuli in our second experiment. This does present some limitations in our study's design but the artworks were of both types—representational (artwork 2) and abstract (artwork 3)—so their inclusion will help us better understand the impact of the type of artwork on individuals' evaluations. Attribution knowledge was the first independent variable in our experiment and the type of the artwork (representational or abstract) served as the second independent variable. Therefore, we have a 2×2 factorial design.

The first factor, attribution knowledge, was manipulated by providing participants information about the artwork before they were exposed to it. Participants were told that they were about to see artwork that was (a) generated entirely using artificial intelligence technology and machine learning algorithms like generative adversarial networks (GANs) and that no human was part of the creative process OR (b) created by a human being by hand on pastel with no technology involved in the entire creative process. This information preceded exposure for all four of the artworks resulting in eight experimental groups into which participants were randomly assigned. Random assignment was done to ensure the error due to personality and other factors not included in our experiment was also randomized. In other words, participants were assigned randomly to one of the eight experimental groups. The second independent variable was manipulated based on the type of artwork the individuals were exposed to as there were two abstract and two representational artworks in the experimental stimuli.

Dependent variables included attitude toward the artwork and purchase intentions along with the nine attributes that were identified in the literature as distinguishing features of art and artwork used in the evaluation of artwork. The nine characteristics on which respondents evaluated the artwork included originality, creativity, expressiveness (degree of expression), aesthetic value, successful communication of ideas, composition, uniqueness, emotional connection, and financial value/worth. These variables were all measured using a 7-point scale where individuals were asked to rate the artwork they just saw on each of the characteristics (1 being lowest and 7 being highest). Attitudes were measured using a 7-point semantic differential scale often used in communication and psychology research (Muehling & Lacznik, 1988) with items such as Good/Bad, Unappealing/Appealing, Pleasant/Unpleasant, and Negative/Positive. Similarly, purchase intentions were also measured using a 7-point semantic differential scale (Mitchell & Olson, 1981) with items such as Unlikely/Likely, Probably/Probably Not, Definitely Would Not/Definitely Would on how likely the respondents were to purchase the artwork they saw if they were in the market to buy some art. At the end of the questionnaire were some demographic questions and another one-item scale that measured individuals' self-reported levels of expertise and knowledge of art on a scale of 1–7 (1 being no knowledge at all and 7 being an expert).

Participants were drawn from Amazon Turk. An invitation to participate in the study was posted on Turk and participants were asked to click on the link provided. Upon clicking on the link, participants were taken to the landing page, which featured an informed consent form. Participants were informed that not all information about the exact or true nature of the study was being presented as that could potentially bias their responses. They were later debriefed about the study's objectives upon completion on the "thank you" page. That page also featured a system-generated MTurk code that they entered

to receive compensation for their participation on the Amazon Turk system. Participants were paid about \$1-\$2 per completion. The entire study took no more than 10 minutes of their time to complete and participants were told that their participation was voluntary and that they could stop at any point during the study. They were also told that all information collected would be analyzed and reported in aggregates and that their anonymity would be protected. The study was approved by the university's Institutional Review Board (IRB) for compliance with Human Subjects research.

The entire questionnaire with embedded artwork was designed using Qualtrics software in English language. The same system was also used to collect and store the data. Once participants agreed to participate in the study by clicking the "proceed" link at the bottom of the informed consent page, they were taken to the page with information about the artwork they were about to see. Post-exposure, dependent variables (attitudes purchase intentions, and variables that measured individuals' evaluation of the artwork) were measured. The questionnaire concluded with some demographic questions.

Results of Study 2

A total of 665 Amazon Turkers attempted to take the survey by clicking on the link provided to them. Initially, about 132 of them failed to pass the attention-testing questions embedded in the survey, which terminated their sessions and marked their responses as incomplete. These responses were deleted from the dataset. Data cleaning techniques were employed to remove speeders (respondents who finished the survey in less than 1/3rd the median time), straight liners, corrupt responses, and incompletes. This resulted in a total of $N = 530$ valid useable responses. Of these 5,30,351 (66%) were male and 179 (34%) were female; 69% of the sample identified themselves as white, 8% as Hispanic, 12% as Asian, 7% as African American, 1.5% as Native American, and a little over 1% as other. In terms of education our sample had 11% high school grads, 13% some college, 7.2% associate's degree, 54.7% bachelor's degree, 10% master's degree, and a little over 1% with professional degrees. The average age of our sample was 35 years with a range of 21 to 79. Lastly, our sample 3.4% making over 150 K, roughly 55% making less than \$50 K, about 35% between 50–100 K, and 6.4% between 100–150 K. Reliability assessment was conducted for all scales using Cronbach's α with all exceeding the generally accepted guideline of 0.70 (Hair et al., 2010, p.118). The mean scores, variances and reliability indices were the following: attitude toward the artwork (4 items, $M = 5.2$, Variance = .001, $\alpha = 0.93$); purchase intentions (4 items, $M = 4.4$, Variance = .024, $\alpha = 0.96$); and evaluation of artwork (9 items, $M = 4.6$, Variance = .10, $\alpha = 0.93$).

In order to examine the role of attribution knowledge and the type of artwork on the three dependent variables—attitudes, purchase intentions, and evaluation

of the artwork, we conducted a MANOVA. Table 2 is a result of the tests of between-subjects effects. As seen in the table, the interaction effect between attribution knowledge and type of artwork is statistically significant for two of the three dependent variables at $p < .05$ level. Given the significant result for interaction effect, the main effects for purchase intentions and evaluation of the ad were not interpreted. Attitudes, on the other hand, were only significant as a main effect for the type of artwork (i.e., differences in attitudes were found between the artworks 1 and 2, both of which were representational, and 3 and 4, both of which were abstract). Participants in our sample rated representational artwork significantly differently from abstract artwork in terms of favorability. To interpret the results and answer our research question, let us examine the Figures 1 and 2, which depict the interaction effect for purchase intentions and evaluation of artwork.

Figures 1 and 2 show the interaction effect such that for the abstract artworks (3 & 4), the evaluation of the artwork in terms of originality, creativity, expressiveness, aesthetic value, successful communication of ideas, composition, uniqueness, emotional connection, and financial value was higher ($M = 4.5$) for correct attributions than for incorrect attribution ($M = 4$). Similarly, for representational artworks (1 & 2), the evaluation of artwork was higher for incorrect attributions than for correct attributions. In terms of purchase intentions, the interaction effect was similar such that participants were more likely to purchase artworks with correct attribution ($M = 4.2$) than incorrect attribution

Table 2. MANOVA Results for Dependent Variables Evaluation of Artwork, Attitude Toward Artwork, Purchase Intentions by Attribution Knowledge and Type of Artwork.

Source	SS	df	MS	F
Evaluation of Artwork				
Intercept	11,581.51	1	11,581.51	7409.14*
Type of Artwork	73.32	1	73.32	46.90*
Attribution Knowledge	4.27	1	4.27	2.73**
Type of Artwork \times Attribution Knowledge	9.38	1	9.38	6.00*
Attitude toward Artwork				
Intercept	14,865.41	1	14,865.41	8682.49*
Type of Artwork	122.88	1	122.88	71.77*
Attribution Knowledge	1.99	1	1.99	1.16
Type of Artwork \times Attribution Knowledge	5.24	1	5.24	3.06**
Purchase Intentions				
Intercept	10,298.16	1	10,298.16	3040.42*
Type of Artwork	115.60	1	115.60	34.13*
Attribution Knowledge	4.67	1	4.67	1.38
Type of Artwork \times Attribution Knowledge	25.17	1	25.17	7.43*

* $p < .05$. ** $p < 0.1$.

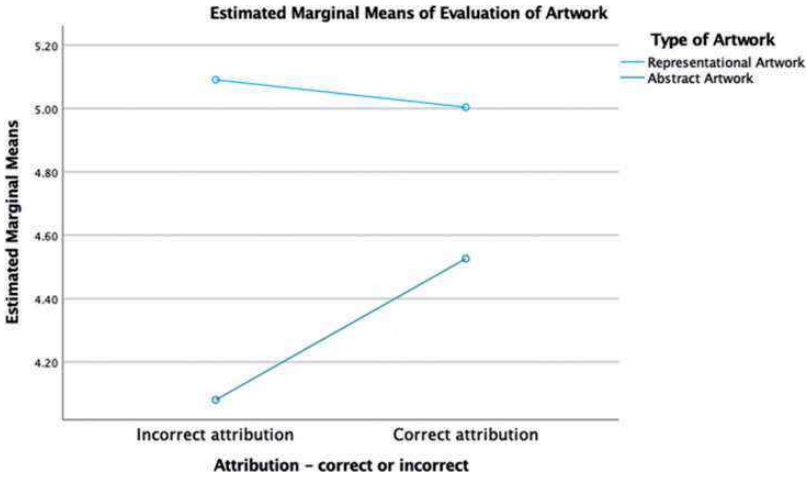


Figure 1. Evaluation of Artwork – Interaction Effect Between Type of Artwork and Attribution Knowledge.

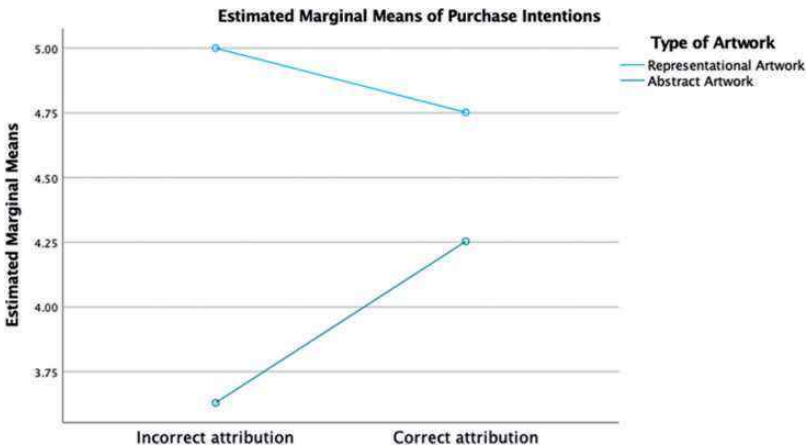


Figure 2. Purchase Intentions – Interaction Effect Between Type of Artwork and Attribution Knowledge.

($M = 3.6$) for abstract artworks 3 & 4, and the purchase intentions were reversed with participants less likely to purchase artworks ($M = 4.7$) with correct attribution than incorrect attribution ($M = 5$) for representational artworks 1 and 2. And all mean differences were significant at $p < .05$ level.

What this means is that there were differences in participants’ evaluation of the artwork and reported purchase intentions based on both (a) information

provided to them about the creator of the artwork i.e., attribution knowledge, and (b) the type of artwork. When the artwork was abstract in nature, correct attribution resulted in more favorable evaluations of the artwork and purchase intentions than incorrect attributions. When the artwork was representational in nature, incorrect attributions resulted in more favorable evaluations and purchase intentions. This result when combined with our findings from study 1 that individuals are more likely to attribute abstract artwork to AI, suggests that when abstract artworks are correctly attributed to AI technologies, it results in more favorable evaluations and purchase intentions than incorrect attributions to humans. On the other hand, in the case of representational artwork, incorrect attributions to humans (despite artwork created by AI technologies) resulted in more favorable evaluations and purchase intentions than correct attributions to AI tech.

In other words, evaluations of artwork, attitudes and purchases intentions depend on both the attribution knowledge and type of artwork (i.e., abstract or representational). What is interesting here is that when the artwork is representational as in the case of artworks 1 and 2, the impact of attribution knowledge was such that machine-made artwork when attributed to humans received more favorable levels of attitudes (artwork 1 $M=5.8$), purchase intentions ($M=5$), and evaluation ($M=5.1$) than when attributed to machines with attitudes ($M=5.5$), purchase intentions ($M=4.3$), and evaluation ($M=4.9$). However, when we ran an independent samples t-test to compare the difference in means and estimate the statistical significance only the difference in purchase intentions was significant at $p < 0.05$ level. Both attitudes and evaluation of artwork were only significant at $p < .10$ level. This suggests that attribution knowledge does play a significant role in influencing individuals evaluations of artwork but that influence depends on the type of artwork.

To sum up, when participants were informed of the creator prior to exposure, this attribution knowledge interacted with the type of artwork (abstract or representational) to influence their evaluation of the artwork and purchase intentions. More precisely, when the artwork was abstract, both evaluation of artwork and purchase intentions were more favorable for correct attribution (e.g., made by machine and attributed to machine) than for incorrect attribution (e.g., made by machine but attributed to human). Conversely, when the artwork is representational, purchase intentions were lower for correct attributions (e.g., made by machine and attributed to machine) than for incorrect attribution (e.g., made by machine but attributed to human).

Conclusion

As AI-generated artwork becomes increasingly common, it is important to better understand audience attitudes toward such artwork and their ultimate

reception and evaluation of it. Through a two-study approach using artwork as stimuli, we investigated (a) whether individuals are able to accurately identify the creators of artworks and (b) the effects of attribution knowledge and type of artwork on the evaluation and reception of artworks. Interestingly, individuals in our study were not able to accurately identify the majority of the artworks in our study. More precisely, they were able to accurately identify only one out of the five AI-generated artworks. Similar to findings in previous studies (e.g., Chamberlain et al. (2018)), individuals in our study 1 also seemed to associate abstract artworks to AI technologies and representational artwork to humans. A number of factors go into the identification and evaluation of artwork including the amount of time and effort that they perceive went into the creation of the artwork (Jucker et al., 2014) and surface-level indicators such as the presence of physical brushstrokes that gives artwork a hand-made quality (Fuchs et al., 2015). Therefore, it is not surprising that the type of artwork has an influence on individuals' evaluation of whether something is created by a human or a machine. Future studies should further examine this and other factors that influence individuals' accurate identification of the creators of artworks.

When participants were informed of the creator of the artwork prior to exposure, this knowledge interacted with the type of artwork such that when artwork was representational a correct attribution resulted in less favorable evaluations and likelihood of purchase. Similarly, when the artwork was abstract in nature, a correct attribution resulted in more favorable evaluations and purchase intentions. What this means for artists is that the type of artwork (abstract or representational) is important as well as the knowledge of who created the artwork in individuals' reception of art. Since individuals associate abstract artwork with computers (findings from our study 1), they are more likely to evaluate them favorably when they are correctly attributed to computers. Similarly, since individuals associate representational artwork with humans, they are less likely to evaluate them favorably even when correctly attributed to computers. This is perhaps because they think that AI and computer algorithms are only capable of producing abstract artwork and not representational artwork yet.

It should also be noted that our study failed to find direct support for a computer-art or AI-generated art bias as attribution knowledge alone did not produce a significant (or interpretable) main effect. Studies have shown that the perceived effort that goes into a work of art influences viewers' perceptions

(Jucker et al., 2014) and people probably do have a negative bias toward AI-generated artwork because it is conceived as requiring less effort. It is possible that this bias could be neutralized by incorrect attribution knowledge and future studies should include the factors that influence individuals' accurate identification of the creators of artwork and relate that to potential bias against such artworks.

Our study has numerous limitations. First, our first study only included two human-made artworks and the identification percentages for both were not vastly different from that of the two extreme AI-generated artworks. This potentially influenced our results to downplay the computer-art bias (i.e., negative bias against AI-generated artwork) and resulted in a failure to find support for such bias. Originally, we did not include more human-made artworks in study 1 because the focus of our study was reception of AI-generated artworks and not human-made artworks. However, in hindsight, this was a mistake as more human-made artworks would have given us a wider distribution of identification percentages. Second, the small sample of stimuli used in study 2 is another limitation, which makes generalization of our results more widely to AI-generated difficult. Although our large sample size might compensate and increase the external validity of our study, the use of non-representative sample of images severely limits the generalization of our results. Third, the artwork used in the study were not pre-tested for representational and abstract types although they can be seen as such based on the content. In retrospect, the artwork should have been pre-rated by naïve viewers to ensure they were perceived as such. Lastly, using only two types of artwork—representational and abstract—is also a limitation of the current study. For instance, drastically different artwork such as non-western art or conceptual art might produce different results. The small range of artwork chosen in this study severely limit the external validity of our results.

Future studies should use more representative samples of art and subjects and also address the other limitations mentioned above. Despite these limitations, it should be noted that our study was designed as exploratory in nature and given the dearth of studies examining evaluations of AI-generated artwork, it serves as the first step toward a better understanding of the role of AI in the creative process and audience reception of AI-generated artworks. We hope that it encourages others to design more robust studies to study this important and inevitable change to how creative works are produced and evaluated in future.

Appendix A. Artwork Used in Study 1.



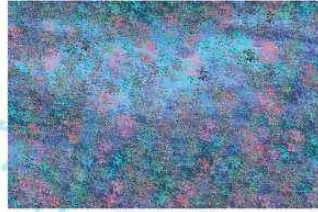
AI-generated



Human-made



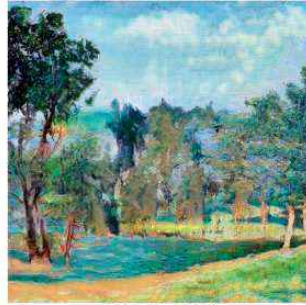
Human-made



AI-generated



AI-generated



AI-generated



AI-generated

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