Artificial Intelligence Art: Attitudes and Perceptions Toward Human Versus Artificial Intelligence Artworks

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Abstract. This research is a study on the young generation views and acceptance of Artificial Intelligence (AI) art based on the painting and literature created by the latest AI technologies to understand AI advancement and capabilities in the domain of art. An online questionnaire is sent to a university's undergraduates in a local university with 202 responds. Data is analyzed by PSPP utilizing Cronbach's Alpha to test the reliability of the questionnaire items. Frequencies, Mean, Chi-Square, and T-Test are used in analyzing the hypotheses. The results show that 54% of respondents did not correctly identify emotions in AI artworks and therefore could not appreciate the emotion expressed in AI artworks. There was no correlation between degree of exposure to AI technology and acceptance of AI artworks although the positive acceptance rate is high - 74%. An average of 55.3% of the respondents are able to correctly differentiate between AI artwork and human artwork. Lastly, there is no correlation between attributed artist identity and judgement on AI images but there is a correlation for AI poem.

Index Terms— ***Artificial Intelligence Art, Emotions in AI Artworks, Artist Identity.***

INTRODUCTION

The term Artificial Intelligence (AI) was originated in the 1950's in modelling human cognition. Nowadays, the term has evolved to refer to application that rely on deep neural networks [7]. AI art refers to artwork made by collaboration between AI algorithms and human artists. There are several common perceptions regarding AI art. Firstly, there is a misconception that AI will never excel in creative arts such as painting and literature and thus will never achieve creativity. This also means that humans have the capability to differentiate between artworks produced by AI versus humans. Therefore, the public should be educated on the roles of AI in artworks and AI creativity though AI might not be able to fully replace human's creativity. On the other hand, humans might not be able to appreciate AI artworks emotionally as they treated it as "artificial". In the previous studies, there are only recordings of human judgements on AI artworks to evaluate how good an AI artworks algorithm is. However, not many focused on how an attributed artist identity might affect the judgement on AI art. Hence, these are the areas that this study wants to investigate. This paper is constructed in four main sections: Literature Review, Research Methodology, Research Results and Discussion, and Conclusion.

LITERATURE REVIEW

What are the roles of AI in art? According to previous studies, AI can be utilized as *Imitator*, *Collaborator*, and *Creator*. AI as an *Imitator* implements the concept of style transfer, which involves the imitation and mixing of existing human artworks [14, 15, 16, 19]. In visual arts style transfer, image-based artistic rendering (IB-AR) techniques are either with or without Convolutional Neural Networks (CNNs) [1, 29, 30]. Techniques without the use of CNNs are typically limited in flexibility, style diversity and effective image structure extractions. In contrary, Neural Style Transfer (NST) utilizes CNNs to extract content information from an image and style information from an artwork. Such content and style information are then combined again to produce the image in the style of the artwork [21]. NST has overcome limitations of non-CNN based techniques because it is not restricted to a limited range of styles.

While AI as an Imitator strives to combine an existing image with an existing art style, the goal of AI as a *Collaborator* is to create novel artworks itself, though with heavy human involvement. In 2018, a painting as the product of human-AI collaboration was auctioned for $432,500 (approximately RM1,716,022) at a British auction house [2]. Technically, the painting was created using Generative Adversarial Networks (GANs) [1]. GANs consist of two algorithms in competition with one another: a generator to produce novel content after being fed with training data, and a discriminator to differentiate the original artworks from the generator's output [23]. The generator tweaks its output until the discriminator can no longer find any difference. In the case of this painting, human intervention comes in at the selection stage, where image outputs were selected based on the human curators' tastes. One advantage of AI art algorithms is that they are constantly learning and improving based on past experiences and training data. Hence, the human-AI collaboration can be a means to maximize both parties' creative capacities in arts [34].

AI as a *Creator* means that other than human effort invested during the process of its learning, no human intervention should occur during its art creation stage, which should eventually produce truly novel artworks [17]. Elgammal's research has dismissed the ability of GANs to produce creative outputs. This is because GAN generators will, under the supervision of the discriminator, ultimately tweak its outputs to an extent that they look like existing artworks. The generator is not pushed to explore the creative conceptual space. Since art creation is tightly knitted with arousal potential of the human emotion [20, 33], GANs, failing at creating artworks that would arouse excitement, cannot produce creative artworks. Therefore, Elgammal proposed a new art-generating system named Creative Adversarial Network (CAN) [17]. CAN is an adaptation of GANs where it also uses the generator and discriminator networks. The difference lies in the training, where the discriminator instead of generator is trained to recognize the styles of artworks. The generator is not fed with any training data but is set to produce random outputs. Then it will receive two feedbacks from the discriminator: whether the output is an art, and how easily the discriminator sorts it into an existing art style. The generator will be rewarded or penalized based on the discriminator's feedback.

The leading definition that is undisputed among researchers for creativity is the ability to generate novel (new) and valuable (useful) ideas [8, 9, 22, 35, 38]. Novelty is categorized into psychological (P-creativity) and historical novelty (H-creativity). P-creativity refers to the generation of an idea that is merely new to the entity that has generated it, whereas H-creativity produces one that is entirely unseen or unheard of in human history. The painting machine AARON that produced vividly original works pursued H-creativity. Its creator Cohen even elevated AARON to the height of a "world-class" colorist [40]. However, computer models most often aim for P-creativity [6]. According to Boden, there are three types of creativity: combinational, exploratory and transformational creativity [4].

Combinational creativity generates new combinations from familiar ideas by identifying indirect associations between two concepts from random sources [25]. For example, Poem.exe generates and posts unique Japanese Haiku poems on Twitter through random combinations of data input. However, AI algorithms face challenges in combinational creativity. There are two aspects to creativity: novelty and value. While Poem.exe can produce new poems every day, many times it generates nonsensical texts. A valuable result should be both interesting and sensible [31, 39]. How can AI art algorithms evaluate the value of their outputs? A possible solution is to introduce creative autonomy for AI machines, so that they evaluate creations independently and change generative standards without explicit direction [28].

Exploratory creativity is where the style and rules are constrained within the conceptual space, but continual learning is needed to seek the space's potential and limits. However, how should AI machines learn? Turing suggests that machines can be developed to simulate a child's mind rather than an adult's [11]. AARON is an epitome of child-learning, seeing that its painting style from 1988 through 2013 had drastically changed. Cohen admits that AARON was like a young child learning how to draw [10].

Transformational creativity includes the alteration of the dimensions that defines the conceptual space, particularly involving the breaking of rules. How can AI art algorithms break rules? Genetic Algorithms (GAs) can be incorporated into the program, which allows random changes that are similar to mutations in biological evolution [5]. In order to avoid radically different changes that causes a discontinuation of style, sculptor William Latham cautiously and sparingly employed GAs in his AI program, eliminating large point mutations altogether. As a result, the series of produced images was artworks beyond himself but remains similar in his artistic style [41].

Can AI excel in artwork production? Back in 1985, AI still lacked of human expression in one of the arts, music-making. However, after decades of evolution, AI is now widely used in audio mastering, even helping students to learn music [3, 32, 36]. Despite huge advancements in AI art, it seems like humans are unable to appreciate or apprehend AI artworks. For example, in the emotion connection to AI artwork researches, participants found that ePainter's paintings is too emotionally depressing [37]. Generative Pre-trained Transformer (GPT) generates writings that still lack of semantic coherence and is difficult to understand [18, 11]. Based on these researches, it is assumed that human still cannot identify emotions in AI artworks. In a study of the "mere exposure" effect, it was found that repeated mere exposure to something will enhance an individual's attitude towards it [12, 24]. Based on this effect, it is assumed that exposure to AI technology will affect one's acceptance of AI artworks. Therefore, this study will focus in undergraduates with higher possibility in AI technologies knowledge exposure.

Finally, bias might affect human judgement on AI art. Reception of AI paintings was positive when human subjects were unaware of the painter's identity [24, 26] When people were told certain paintings were created by AI (attributed artist identity = AI), they rated the paintings significantly lower than other people who thought the artist was human (attributed artist identity = human) in terms of composition, degree of expression and aesthetic value [27]. Hence, we want to replicate the experiment and find out how attributed artist identity might affect the judgement on AI art.

RESEARCH METHODOLOGY

Online questionnaire is selected to collect data due to the COVID-19 pandemic. The questionnaire consists of five sections. Section 1 is about demographic background of respondents which includes respondent's age, gender and faculty. Section 2 collect general impression of respondents on AI artworks in terms of emotions. Four AI paintings that look the same but with different color palettes were used in the questions. Respondents selected one from four phrases that best described the painting's emotions (Figure 1). These four paintings are adapted from Salevati and DiPaola [13, 37].

(a) Happy/Excited/Delighted

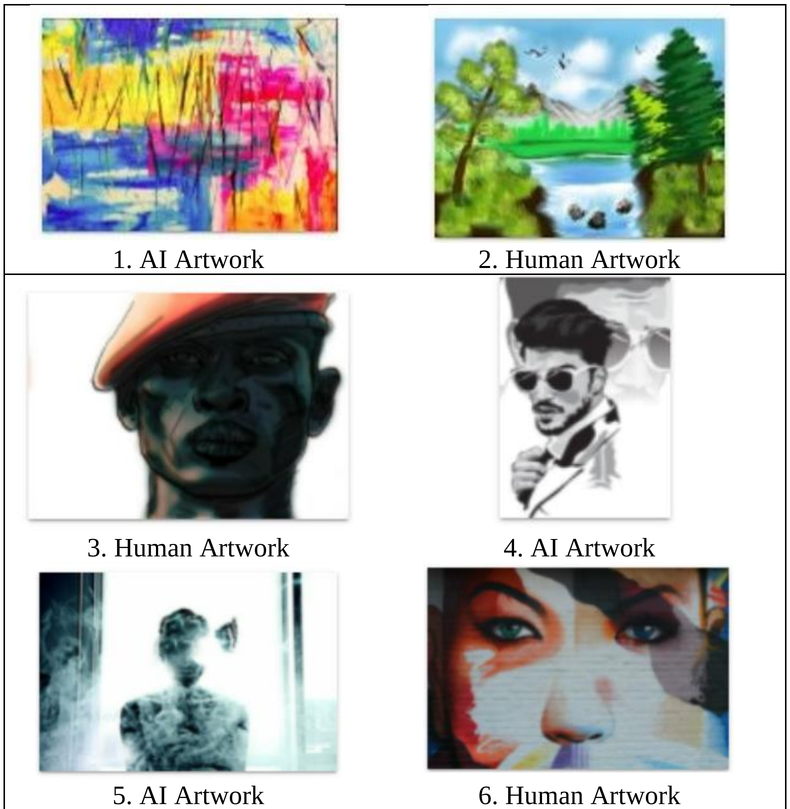
(b) Sad/Tired/Bored

(c) Calm/Satisfied/Relaxed

(d) Afraid/Frustrated/Angry

FIGURE 1. Images of AI artworks adopted from Salevati and DiPaola [13, 37].

Section 3 is a Turing test which is used to test whether respondents could pick the correct artwork produced by AI [11]. Three pairs of paintings (Figure 2) and one pair of poems were used. In each pair, one was produced by AI and another was by human. Respondents are required to identify artwork produced by AI.



Source:
1. https://www.pexels.com/photo/photo-of-abstract-painting-on-canvas-1626364/
2. https://fineartamerica.com/art/paintings/river+tree
3. https://www.artmajeur.com/en/letsfly/artworks/13153904/african-soldier
4. https://pixabay.com/vectors/guy-male-person-young-face-4541015/
5. https://pxhere.com/en/photo/603005
6. https://blogs.lse.ac.uk/vaw/

FIGURE 2. Human artworks and AI artworks used in Turing Test.

Section 4 is about personal opinion which elicit the degree of exposure to AI technology and the respondents' acceptance of AI artworks. The questions to determine the acceptance variable were taken from the research done by Hong and Curran [26, 27]. These four sections (one – four) are non-experimental design. Section 5 was an experimental design to find out the relationship between attributed artist identity and respondents' judgement on AI artworks. This design was modified from Hong and Curran's research [26, 27]. Section (5) has five questions that involved three paintings and two writings produced by AI. In questionnaire set A, respondents were told that these artworks were produced by AI. In questionnaire set B, respondents were told that these artworks were produced by human. Respondents were required to rate the artworks on a five-point Likert scale on several evaluation criteria. Evaluation criteria were inspired by Hong and Curran's research [26, 27] and Elkins and Chan [18].

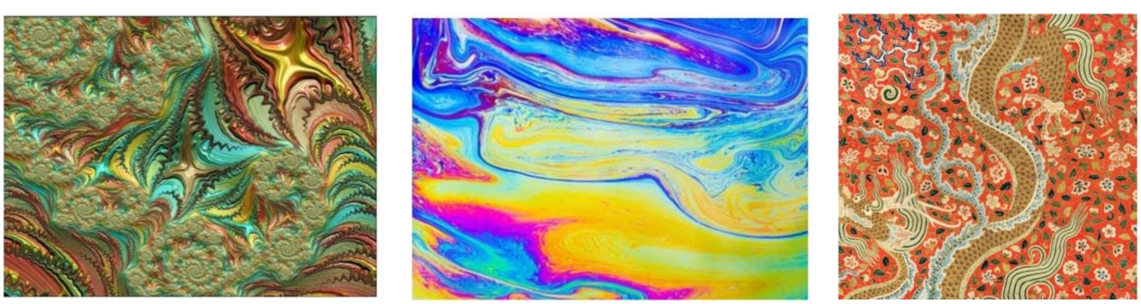


FIGURE 3. Examples of AI artworks used in Section 5 modified from Hong and Curran's research [26, 27].

Based on the literature review, this study's hypotheses are constructed as follows:
H1: Undergraduates are not able to identify emotions in AI artworks.
H2: There is a correlation between degree of exposure to AI technology and acceptance of AI artworks.
H3: Undergraduates are able to correctly identify human artwork versus AI artworks.
H4: There is a correlation between attributed artist identity and judgement on AI artworks.

RESULTS AND DISCUSSION

A pilot test is conducted on five college students before the questionnaire is distributed online through social media, email and WhatsApp. The reliability of the questionnaire items is also tested using Cronbach's Alpha test utilizing PSPP with the result of $N = 47$, $\alpha = 0.87$, which indicates a high reliability.

Demographics

Table 1 shows a total of 202 respondents demographics: age, gender, and faculty (Questionnaire Section 1). From the data, most of respondents are male from FOCS as there are majority of male in the faculty.

TABLE 1. Respondents' demographics data.

		No. of Respondents	**Percentage (%)**
Age	<18	1	0.5
	18-20	85	42.1
	21-25	115	56.9
	>25	1	0.5
Gender	Male	106	52.5
	Female	96	47.5
Faculty	FOCS	111	55
	FAFB	51	25.2
	FOET	2	1
	FSSH	14	6.9
	FCCI	8	4
	FOBE	6	3
	FOAS	10	5

FOCS: Faculty of Computing and Information Technology
FAFB: Faculty of Accountancy, Finance and Business
FOET: Faculty of Engineering and Technology
FSSH: Faculty of Social Science and Humanities
FCCI: Faculty of Communication and Creative Industries
FOBE: Faculty of Built Environment
FOAS: Faculty of Applied Sciences

Results of Each Hypotheses Test

H1: Undergraduates are not able to identify emotions in AI artworks.

In the questionnaire Section 2, the portraits in questions 1 and 2 are the same images but modified with different color palettes. Each color palette was developed by researchers Salevati and DiPaola [13, 37] to convey a specific emotion (intended emotion). Respondents are given four groups of phrases that described the emotions: 1. Happy/Excited/Delighted, 2. Calm/Satisfied/Relaxed, 3. Sad/Tired/Bored, 4. Afraid/Frustrated/Angry. Respondents are required to choose the group of phrases that closely resembled what they felt from the paintings. If the chosen group of emotions did not correspond to the intended emotion, the response is counted as "emotion not correctly identified". The purpose of this section is to prove that respondents are not able to appreciate/identify the emotions expressed in AI artworks. Result of the experiment shows that 54% (mean) of the undergraduates cannot identify the intended emotion correct (Table 2). This shows that despised the advancement of AI artworks, human's apprehension of the artworks is not aligned and therefore more researches are required to improve in this context. Based on Table 2, H1 is accepted.

TABLE 2. Respondents' identification of emotions in AI artworks.

Questionnaire Question	Respondents Who Did Not Identify Emotion Correctly	
	Number of Respondents	**Percentage of Respondents**
Q1 Left Portrait	129	64%
Q1 Right Portrait	106	52%
Q2 Left Portrait	137	68%
Q2 Right Portrait	62	31%
Mean	109	**54%**

H2: There is a correlation between degree of exposure to AI technology and acceptance of AI artworks.

Based on Table 3, respondents have moderate exposure to AI technology (Mean = 3.33). Table 4 shows the acceptance rate of AI artworks and the mean is 74.9%. However, based on Table 5, there is no significant correlation between degree of exposure to AI technology and acceptance of AI artworks. Therefore, H2 is rejected. This result is different from the theory proposed by Zajonc's "Mere Exposure Effect" [12].

TABLE 3. Respondents' degree of exposure to AI technology.

Degree of exposure	Number of Respondents	Percentage (%) of Respondents
Barely heard of	5	2
Heard of	27	13
Neutral	83	41
Know a lot	70	35
Know a great deal	17	8
MEAN	**3.33**	

TABLE 4. Acceptance rate of AI artworks.

Questionnaire Items to test the acceptance rate of AI artworks	Percentage of Yes/Positive Response
Q1. "Based on your impression on AI art on previous questions, do you think AI artworks can compete with human artworks?"	Yes (61.4%)
Q2. "If AI is able to consistently produce artworks whose quality is as good as humans, will you acknowledge AI as a creator of creative art (e.g. AI artist)?"	Yes (61.9%)
Q3. "Based on your personal view, what role do you think is most suitable for AI in the creative arts industry?"	Positive Response (95.5%)
Q4. "Which word describes your feeling about contemporary AI artwork most accurately?"	Positive Response (80.7%)
MEANS	**74.9%**

TABLE 5. Ch-square test for the relationship between acceptance rate and degree of exposure.

	Pearson Chi-Square	Asymptotic Sig. (2-tailed)
Q1 x Rate	1.92	0.751
Q2 x Rate	2.65	0.619
Q3 x Rate	17.14	0.144
Q4 x Rate	9.17	0.689

H3: Undergraduates are able to correctly identify human artwork versus AI artworks.

Section 3 is a Turing test based on 8 images. Respondents are required to compare two images created by AI artwork and human artwork [11]. Based on Table 6, an average of 55.3% of the respondents are able to correctly differentiate between AI artwork and human artwork. Therefore, H3 is accepted.

TABLE 6. Turing test – differentiate between AI artwork and human artwork.

	Total Number of Respondents identify correctly	Total Percentage of Respondents identify correctly
Q1. Image 1 & 2	75	37%
Q2. Image 3 & 4	126	62%
Q3. Image 5 & 6	134	66%
Q4. Image 7 & 8	83	41%
MEAN		**55.3%**

H4: There is a correlation between attributed artist identity and judgement on AI artworks.

In this experimental test, respondents are informed that the images in a subsection are created by AI. Respondents have to judge the images accordingly. In the next subsection, AI artworks are shown to the respondents but respondents are informed that these images are produced by human artists. For each attributed identity group, the human artist identity group consistently gain slightly higher ratings compared to the AI artist identity group (Table 8). Based on the independent Sample T-Test, there is a relationship between attributed artwork and judgement on AI artwork for Poem only (Table 7). Since not all evaluation criteria have significant differences in means, therefore H4 is rejected.

TABLE 7. Independent Sample T-Test for attributed artist identity and judgement on artworks

Evaluation Items	F	Sig (2-tailed)
Image 1	0.33	0.054
Image 2	0.65	0.268
Image 3	0.39	0.223
Poem	6.00	0.024
Writing	5.36	0.540

TABLE 8. Mean of ratings comparison between groups informed on "Human" artist identify versus "AI" artist identity

Evaluation Items	"Human" artist identity	"AI" artist identity
Image 1	3.77	3.59
Image 2	3.38	3.26
Image 3	3.84	3.71
Poem	3.76	3.54
Writing	3.73	3.79
Mean	**3.70**	**3.60**

CONCLUSION

This study has combined several experiments from previous studies regarding human attitudes and perceptions towards AI artworks. The findings are interesting in which most of the result did not comply with previous studies. For example, there is no relationship between exposure of AI and acceptance of AI artworks. There is also no relationship between attributed artwork and judgement on AI artwork. This has proven that researchers can focus in improving AI algorithm in order to produce more realistic artworks as the acceptance and judgement of AI artwork is not based on one's AI knowledge or exposure to AI as arts is a field of feelings and it depends on different individuals' experience and personal preference.

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