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Table of Content

1. Introduction

“Well," said Pooh, "what I like best," and then he had to stop and think. Because although Eating Honey was a very good thing to do, there was a moment just before you began to eat it which was better than when you were, but he didn't know what it was called.”
― A. A. Milne, Winnie-the-Pooh (1926)

In everyday situations, anticipation of events is a frequent occurrence. Already feeling the excitement when waiting for the beginning of a concert and for the band to appear on stage, anticipating how food will taste based on how it looks and smells, or even anticipating how a conversation will go based on the nature of the topic are all everyday situations that demonstrate how common and important anticipation is in our lives. These expectations can influence how we react, interact or even how we interpret the outcomes of any situation that we predicted in our minds. Research about predictive coding (e.g., Clark, 2013) has highlighted the importance of studying anticipation and expectation in various contexts, like art (e.g., Van de Cruys & Wagemans, 2011) or even agency detection (Andersen, 2016). Expectation in art is crucial for the actual art experience, as people anticipate a rewarding experience on a neuronal level even before viewing art, which then shapes the assessment of the objects presented (Kirk et al., 2009, Lacey et al., 2011). However, other aspects of anticipation might be involved in the engagement with art:

An intriguing question remains whether the expectation of art made by a human artist or computer generated art impacts the viewing experience because people might anticipate human connection to the art like empathy and communication. Since this connection between artist and viewer is regarded as a key aspect of art appraisal (e.g., Gerger et al. 2018, Pelowski et al., 2018) we want to expand the monitoring of brain activity signalling art anticipation to empathy and perspective-taking. Corresponding brain areas have been found to be activated when viewing art (Kühnapfel, 2020) yet it has never been researched whether viewers prepare for an interaction with art expecting this social connection to the artist, making an art experience not only a rewarding but also a social experience.

To investigate this, we aim to answer the following questions with our research:

1. Does anticipation of a human sender or artist impact brain activity before (and during) viewing art?
2. Do activation patterns change based on the design of the actual artwork?

After monitoring the anticipation and expectation of the art, we incorporated digital art made by humans and by computers, with most pictures looking highly similar, as well as more complex representational landscape art, also made by humans or with an AI to get a nuanced insight into viewers' reactions. This way, we can investigate whether participants believe the prime and appraise the stimulus according to the contextual information or whether reactions are adapted to the appearing stimulus if participants sense an incongruence between prime and picture. Will contextual information about the "humanness" of the artist manipulate viewer's opinions or will they be able to look through the framing and sense the art or the humanness of the artist regardless of the label provided?

We want to explore differences in appreciation, perceived intention and emotional connection to art made by human artists and to highly similar computer generated art behaviourally and neuronally, thus giving insight into how much the concept of a human artist influences the anticipation of viewing art and the reaction to the stimuli. While there is some behavioural data towards this question (Demmer, 2021), there is still little empirical evidence and brain data in this area of empathic connection and perceived intention. Answering these questions will add to the empirical evidence surrounding the relationship between context, anticipation and empathy in art appraisal. Moreover, the design of the study will provide new insights into the differences of evaluation between art categories with varying degrees of complexity and authorship. In the following, relevant research on labelling and context, authenticity of art, the agency problem of AI art, and emotion transmission in art are presented before connecting these topics to neuroaesthetics. Then, we will introduce the methods of our research before displaying the results and putting them into the context of existing research and findings.

2. Literature Review

2.1 Expectation and Anticipation of an Aesthetic Experience & The Effect of Framing

The taking in of art has been depicted in specific models that explain the multiple stages of processing, including visual processing, classification of a stimulus as art, cognitive mastering and forming judgements and experiencing emotions in an evaluation stage. While differing to some degree, most models of art appraisal agree that context, expectations and information on an artwork affect aesthetic processing in some measure (e.g., Leder et al.,et al., 2017, for a review see Pelowski et al., 2016). Even before viewing art, expectations can be shaped of what kind of context viewers are seeing an artwork in or what kind of artwork they might be expecting, for example through providing information or labelling. There are various forms of expectation or anticipation in connection with viewing art: In the VIMAP art model (Pelowski et al., 2017a), the first stage is defined as pre-classification and refers to the state before engaging with art. Among individual-based factors like personality, this stage includes the viewing context (museum, laboratory etc.) and the kind of stimuli that are expected. In case of viewing art this means that people anticipate that they are about to enter a situation involving art in some form. Such a belief leads to an expectation of pleasure and reward and to the onset of an *"'aesthetic' focus"* (Pelowski et al., 2017a, p. 86) which describes developing a distanced, less questioning attitude towards relevance or practical use of an object while being more attentive to its style, and to increased liking and aesthetic rating of the artworks. (e.g. Leder et al., 2004; Pelowski et al., 2017a; Gerger et al., 2014). To illustrate, this attitude allows viewers to find aesthetic experiences even in artifacts that would not be considered art in an everyday setting. Framing stimuli as art gives the brain cues and indications on what to expect, how to anticipate and process these stimuli, respond to and interpret them (Kirk et al., 2020, Szubielska et al., 2020). For example, if viewers are expecting an art context, people adapt their processing to putting more focus on form and style of the stimuli than in a non-art context (Jacobsen et al., 2006; Cupchik et al., 2009). This ranges from non-aesthetic objects, like the often-mentioned example of a readymade urinal being placed in an exhibition (Douchamp's 'Fountain', 1917) to even highly aversive stimuli, which can be appreciated when expecting an art setting due to the emotionally distanced status of art appraisal (Gerger et al., 2014).

These expectations viewers have through framing or providing context are a powerful tool to shaping people's reactions towards the art presented. There has been a lot of research on the question whether framing alone can influence people's expectations and reactions to art or whether art has a unique quality that stands out through labelling or priming. Research on both positions is presented in the following sections.

2.1.1 The Influence of Framing and Labelling on Anticipating and Experiencing Art

Framing stimuli as art is powerful enough to not only alter people's understanding and interpretation of images, but also their expectation and their emotional experience. For example, titles influence the processing of artworks because they are an information source that helps to understand or interpret the artwork – especially in abstract art (Leder et al., 2005). Titles and information about the artwork encourage viewers to assign meaning to the artwork and looking for the artist's intention. Apart from understanding, contextual information can even influence liking. According to fluency theory, easier processing – for example when a title provides information about an artwork – can lead to a more positive aesthetic experience and to higher liking of the picture (Gerger & Leder, 2015; Belke et al., 2010). Aligning with this, Szubielska et al. (2020) found that information about an artist's disability increased people's liking of ambiguous artworks compared to the same artworks without such contextual information about the artist. Information like this increases the understanding of art, which facilitates its processing and therefore leads to higher appreciation of the piece (Szubielska et al., 2020). Even children consider information about an artist's impairment, like a broken arm for example, and then shift their evaluation criteria to the intention of the artwork rather than the actual content and they are more tolerant with ambiguity or with the intended content of the artwork (Bloom & Markson, 1998).

2.1.2 Uniqueness of Human Art

While labelling and context can nudge viewers' interpretations of artworks, some experiments studying the classification of stimuli as art with labelling imply a property of art that cannot be manipulated by framing. This contrasting evidence is crucial for our project, as we mainly investigate the expectation before viewing art, which is heavily influenced by framing. We ask whether viewers react according to the label or whether there is something special in the art that is powerful enough to overwrite the prime and the expectation and thus shift the responses to match the actual stimulus upon seeing it.

There are several studies suggesting a fundamental component of art that can be intuitively detected and classified as art, even with misleading labelling. For example, Hawley-Dolan & Winner (2011) found that people do have the ability to distinguish original abstract art by professional artists from similar looking paintings by children or even animals, regardless of the context provided. Thus, people rated professional artworks as the objectively better pieces. However, this acknowledgement of quality did not necessarily affect or was not reflected in the subjective ratings, as liking was not significantly higher for pieces by professional artists (Hawley-Dolan & Winner, 2011). Strikingly similar results were found by Snapper et al. (2015) with the same stimuli set but a different experimental setup. Even pigeons can be trained to distinguish between professional abstract art and children's art (Watanabe, 2001). Going one step further, these animals can be trained to distinguish children's artworks with a higher artistic quality from ones with lower artistic quality (Watanabe, 2010). Thus, there seems to be some objective underlying mechanism or characteristics to art that can even be detected by animals that certainly do not share the human intuition and perspective on art and aesthetics in general, and that are not fully affected by framing effects (Watanabe, 2010).

A major part of our project is providing more evidence to this question, whether the prime and expectation or the nature of the stimulus are crucial to the art experience. Since processing art is more complex and there is evidence for both explanations, we also consider an interaction between the impact of the label combined with the expectation prior to viewing and the impact of actually viewing the stimulus.

2.2 Framing in Generative and AI Art

The present project focuses on generative art, so art made with or by artificial intelligence, which makes this innate and detectable quality of art made by human artists a special interest for this study. There is conflicting evidence whether viewers can distinguish art made by an AI from art made by human artists, which leaves the question whether generative art can also hold a similar innate quality or whether this is unique to art made by a human artist without generative tools:

Elgammal et al. (2017) tested whether people could distinguish human art from art made by an advanced AI and discovered that the label held stronger influence on people's assessment than the ability to distinguish the pieces. If not labelled correctly, participants were not able to distinguish AI art from human art (Elgammal et al., 2017). However, other studies provide contrasting insights into people's ability to distinguish human art and AI art. In a similar setup, Hong & Curran (2019) found that the quality of human art was rated higher than of AI art ("composition", "degree of expression", "aesthetic value"), regardless of the label (human/AI).

This distinction of human and AI art supports the notion of a uniqueness in human art that can be detected even in a deceptive context, and – if aspired – can serve as a goal for AI to produce more human-like, and therefore considered more creative, art (Hong & Curran, 2019). This discrepancy of results provides intriguing motivation to study the question whether people are inherently able to distinguish computer-made from human art. The following section discusses why this distinction might be diffuse for viewers and how this might affect their expectation and anticipation of human and AI art.

2.3 Agency, Authorship and AI – The Crux of the Mind behind the Art

Research about people's reaction and attitude towards computer creations and AI has been done even before AI methods advanced rapidly over the last few years. Generally, ascription of goals, features and thought patterns is a bias of the human mind that helps in understanding other humans, but has been shown to extend to non-living objects, like animated game avatars (Müller et al., 2018) or even simple shapes (Heider & Simmel, 1944). Nass & Moon (2000) found that people tend to apply social rules to computers and Sundar & Nass (2000) showed that people tend to separate programs from their programmers, treating the interface as an independent existence. Connecting this phenomenon to art and especially art created with or by a computer or an AI, viewers might look for a connection with the "mind" behind the artwork, through the artwork. Foucault (2019) suggests that the real source or artist is not as crucial for the art experience and the connection to the art as a perceived source, which in this case might be a computer or an AI. Findings by Demmer (2021) even suggest emotional responses and ascribing intentions when viewing completely randomly generated computer images, which can be explained with viewers' tendency to ascribe agency to the computer as an artist.

Since the possibilities and features of AI has advanced rapidly over the last years, there are varying opinions and standpoints about its role in art: Questions of agency, authorship, emotional connection and creativity in regard to using AI to create art elicit contrasting standpoints and opinions. Neither the advancement from graphics (e.g. art by Georg Nees, Frieder Nake, Vera Molnár) to complex art made by or with an AI nor the time passed since the first works of art made with a computer or AI have changed the discord in this discussion - if anything the debate has grown more complex with new advancements of AI. Varying opinions circle around autonomy of AI and authorship of the artwork. Some consider AI as a mere tool for an artist, comparing it to brushes, a camera or any digital artwork produced with a computer (e.g., Hertzmann, 2018, Christie's, 2019, 03:55:40). AI artist Mario Klingemann asks pointedly: *"Would you ask a pianist if his piano was the author of the piece?"* (Klingemann, 2018) Others ascribe AI some form of autonomy and suggest a collaboration between the artist and the AI (e.g., Chung 2019, 13:30, Elgammal & Mazzone, 2020). Still others want to refer to AI as an artist itself, which includes attribution of autonomy and creativity and potentially puts AI more in the role of a competitor to the artist (e.g., Colton 2012, Miller 2020). With this spectrum of conceptions, ardent and unresolved discussions are hardly surprising. Whole exhibitions, like "Götzendämmerung" in the Haus der Kunst in Munich (2020) or summits and conferences like the Art + Tech Summits held by Christie's have been dedicated to dilemmas of authorship and copyright, however there is no universal answer – just like there is no universal definition of art itself.

The discrepancy of opinions surfaces most clearly when AI art is sold for high prices. The first artwork made by an AI – a portrait generated from old masters' style portraits called 'The portrait of Edmond de Belamy'- that was officially sold at Christie's in 2018 reached an expectation-exceeding price of around 430.000$ and sparked a polarising wave of discussion around the topic of generative art and of authorship, with reactions ranging from satisfied and eager to frustrated and confused (Christie's, 2018, Bailey, 2018, Bailey, 2019a, Jones 2018).

The polarising debate about those topics demonstrates that AI might reinvent the meaning of art in the coming decades, since it is a new and provoking medium and style. Art can be seen as a mirror of society and as a product of the possibilities the current generation has access to. Since artists are often looking for ways to reinvent or open new branches in the creation process, computers and AI are just the next step to extend the potential of artistry (Bailey, 2019b, Christie's, 2019, Chen et al., 2020). This tentativeness towards both the process and the product of AI art and the small amount of empirical research that has been done on humans' opinions and reactions toward it provide the foundation of our research questions.

2.4 The Value of Authenticity in Art and its Relation to Labelling and AI

Especially when considering early art entirely made by an AI, a common judgement or critique is a lack of artistic or emotional value and of communicational elements (e.g., Jones, 2018, Saltz, 2018). In many opinion pieces and articles about AI art, the issue of its authenticity and originality arises by questioning whether the methods and algorithms can create original and thus authentic art (e.g., Chambers, 2020). The following section considers why the perceived authenticity and originality is such an important aspect for an art viewer and how this relates to AI art.

Questions of authenticity have a high priority in the art world. For example, a topic of debate is whether heavily restored art can even still be considered as authentic and original or whether the influence of the restorer has interfered with the originality and authorship of the artwork (for a review of the 'Facsimile Debate', see Uchill, 2015). An extreme example is the case of a painting called "Salvator Mundi", which has been claimed to be a long-lost original artwork by Leonardo da Vinci. The painting was considerably damaged and was restored heavily before its authenticity as a 'Lost Leonardo' was officially examined. Aside from medial and political attention and the doubt whether the picture was an original Leonardo da Vinci in the first place, the heavy restauration process sparked a series of arguments that claimed the restorer to either have created an original on their own or to have restored it so much in the fashion and style of Leonardo da Vinci that any chance of authentication has been made impossible (Koefoed, 2021). This critique was most strongly voiced when the painting was promoted by Christie's for an auction, and in succession reached a sky-rocketing price of 450 million US Dollars. Like with the portrait of Edmond de Belamy, the price of the Salvator Mundi aggravated critics who question the authenticity or the authorship of the painting (Koefoed, 2021). Thus, the unsure authenticity status yielded similar reactions to the AI nature of the portrait of Edmond Belamy and shows a connection to questions of authorship and copyright that arise with AI art. Looking at data, a similar connection can be made: Artworks labelled as original elicit higher appraisal ratings than art labelled as replica or fake (Wolz & Carbon, 2014). Corresponding to this bias, artworks labelled to be from a gallery evoke higher liking than artworks with the label to be generated with a computer program (Kirk et al., 2009).

Newman & Bloom (2011) suggest and explore some reasons for this insistence and bias towards authentic and original art. An artwork is characterised as a unique piece that took time and effort to be manufactured. In the study, original artworks and their identical duplicates are compared to mass-produced artifacts and their identical copies. Transferring this set-up to original human art compared to AI art, the effort AI art might take (like building a suitable algorithm, code and training set) is usually not grasped by viewers, so the expenditure of time can seem to viewers as only a fraction compared to the time an artist using no AI puts into their work. Moreover, since working with a code, viewers could believe that the methods used in AI art can be reproduced exactly, whereas it seems more difficult to copy every material, method used and even every brushstroke of an analogous piece of art. Another point Newman & Bloom explore is that an artwork is valued more if there is some form of physical contact with the original artist. This theory is based on the "law of contagion", stating that objects, in this case artworks, take on a certain quality by the original creator (Newman & Bloom, 2011).

Our study strives to put these attitudes towards authenticity into the context of AI art, since critique of AI art has incorporated the argument of its unoriginality (Chambers, 2020). We examine whether the theories about effort or traces of the artist influence what viewers expect or anticipate when preparing to view art made by human artists and AI art. These arguments are related to art as a means of emotion and a bridge of interaction between the artist and the viewer, which will be discussed in the following section.

2.5 Emotion Transmission, Empathy and Intention

"A work of art which does not begin in emotion is not art." – Paul Cézanne

Even though there is no clear definition of art and what makes a picture art, a considerable number of conceptions share that creating art requires intention and that it is a means of emotional communication, or at least a representation of emotion (e.g., Menninghaus et al., 2019, Pelowski et al., 2017a, Snapper et al., 2015). In our project, one of the principal aspects are interested in is the expectation and anticipation this facet of art viewing might elicit. When viewers are prepared and expect to view art by a human artist, we investigate whether the bias to ascribe agency and the emotional connection that might be crucial to the art experience develop during the sole expectation and anticipation, so even before viewing the actual art.

While the general idea that emotional connection and a form of empathy are a part of experiencing art has been discussed even in greek philosophy and later in German aesthetics of the 19th century (for a review see Pelowski et al., 2018 p.1 and Menninghaus et al., 2019 p.1), recent research has been focussing more on this aspect of the art experience again. The basis of any emotional connection is empathy. Being closely connected to Theory of Mind (ToM), it is defined as understanding other people's experiences from their point of view (e.g., Hardee, 2003). Attributing goal-directed behaviour and mental states like beliefs or intentions to another human being is linked to cognition and internal states. This form of cognitive empathy is associated with perspective-taking, mentalizing and Theory of Mind (Trapp et al., 2018). Connecting this concept to art, the viewer considers the artist's mind and thought processes and tries to infer the artist's intention behind the artwork. This process is key to understanding, getting involved with and appreciating art (Hawley-Dolan & Winner, 2011, Jucker & Barrett, 2011). Grasping the intention of an artwork does not necessarily have to be content-related or obvious: Abstract or non-representational art is frequently fulminated against on account of not requiring skill and lacking effort. At first, the intention of the artist might stay hidden for some viewers because it is not displayed in the content of the picture (Snapper et al., 2015). However, Snapper et al. (2015) shows that people can perceive intention and skill even in seemingly structureless art and if they do, they enter a state of connecting to the artist.

Besides understanding intention, empathy can also refer to affective states, resulting in genuinely experiencing the internal state or feelings of others. This can alter the own affective state by adjusting to what emotions the other person is experiencing (Trapp et al., 2018). The concept of affective empathy stems from the German term "Einfühlung", which translates to "feeling into" and appeared in the context of experiencing embodied sensations related to formal, contentual or emotional aspects of art in the 19^{th} century (Freedberg & Gallese 2007; Gerger et al., 2018). Since then, empathy and feeling into have been argued to be essential for both creating and experiencing art (Gerger et al. 2018, Pelowski et al., 2018). With a higher ability to feel into and to empathise comes a deeper, more pleasant and more moving engagement with art (Freedberg & Gallese, 2007; Gerger et al., 2018; Pelowski et al., 2018). Even more, empathy does not occur solely on the viewers', but also on the artists' side. Thus, art might have the potential to act as a link or medium for empathic connections or communication between the creator and the receiver even in the absence of the artist (Pelowski et al., 2018). Art connects the emotions the artists put into the artwork (either by feeling something themselves or in the content of the picture) and the emotions the viewer picks up when viewing the artwork. This process of transmitting emotions is arguably one of the most important criteria and purposes of art, and maybe even the core of aesthetic experiences (Freedberg & Gallese, 2007, Gerger et al., 2017).

The priorly mentioned studies asking people to distinguish professional abstract art from children's drawings (Watanabe 2001, Watanabe 2010, Hawley-Dolan & Winner, 2011, Snapper et al., 2015) suggest that one reason for the ability to differentiate the pictures regardless of the label is because the participants were able to sense the artists' intention through the professional artworks (Hawley-Dolan & Winner 2011, Snapper et al., 2015). Thus, social and empathic factors might influence the human perception of art, perhaps even stronger than labelling alone. This makes the empathic bridge a crucial topic to explore in the anticipation of viewing art because it might reveal whether viewers prepare for this intrinsic human art quality and the connection through the artwork even before viewing art.

2.6 Neuroaesthetics and Expectation in the Brain

It is difficult to observe what people feel during a period of expectation with just behavioural ratings, so monitoring this expectation period with brain imaging is beneficial. Imaging data adds a crucial layer of empirical data to surveying the empathic anticipation of art and can put behavioural data into context. Especially the role of context in aesthetic appraisal has been redefined due to neural evidence (Pearce et al., 2016), which is why brain imaging is a crucial part of the present project. Demmer (2021) suggests a neural examination of empathy regions in preparation to viewing art, following findings that highlight the importance of neural investigations of expectation and preparation to viewing art:

For example, a certain expectation or anticipation of reward has been found when participants prepare to view stimuli presented as art as opposed to stimuli presented as non-art or computer generated art (Kirk et al., 2009, Lacey et al., 2011). These studies show that brain areas related to vision, reward-related areas and areas associated with assigning hedonic value activate while preparing to view art and stay activated while viewing art. Kirk et al. (2009) provided participants with modulated context of expecting either an artwork from a gallery or a computer generated artwork. While the pictures were the same, the context fuelled different anticipatory reactions in the brain. For the gallery context, there was more expectation of hedonic value – and therefore more activation in the corresponding brain area - than for the computer generated context. This pattern was mirrored behaviourally, as people rated gallery-labelled pictures with a higher aesthetic value than computer-labelled pictures. Lacey et al. (2011) found that reward processing is an essential part of the neural processing of art. Moreover, in accordance with the context modulation in Kirk et al. (2009), the reward circuitry, including the ventral striatum, the hypothalamus and the orbitofrontal cortex, is activated by artistic status alone and is not influenced by the actual content or style of the artwork (Lacey et al., 2011). Compiling the results discussed, framing stimuli as art fosters the expectation of a rewarding and positive emotional experience.

Besides reward-related areas, motor areas have been shown to activate when understanding and feeling into art. This especially applies to visual art containing a notable trace of the artist or remnants of the creation process, like brush strokes or general texture of the painting, and can be attributed to embodiment (e.g., Umilta et al., 2012, Sbriscia-Fioretti et al., 2013). Freedberg & Gallese (2007) incited a surge of studies examining embodied reactions of emotional processes and sensations in art appraisal. Embodiment is a mirroring mechanism that activates internal representations of emotions or sensations that we see in social stimuli, facilitating empathic and emotional engagement with the stimulus. When observing gestures or movement, the same motor representations needed for these movements and motor acts are activated in the observer. Even static images showing movement (i.e., a picture of someone moving) can elicit the same motor representations needed for the depicted movement.

Applied specifically to art, Freedberg & Gallese (2007) suggest visible traces of the artist as observed action in non-representational art that is mirrored in brain activation of the viewer. Viewers perceive such traces as a reminiscence of and therefore connection to the artist and as evidence of authenticity (Pelowski et al., 2017b). Previously mentioned, Newman & Bloom (2011) identify perceived physical contact with the artist as important component for anticipated authenticity, with the traces of the artist being evidence for this ‘contagion quality’ of art. Umilta et al. (2012) collected neural responses when viewing original artworks with clear traces of the artistic process (slashes in the canvas, heavy brush strokes etc.) and when observing modified versions of the same artworks, where the pictures were reproduced digitally to remove traces (i.e., slashes became simple black lines). Results confirmed that the original artworks elicited more motor activation than the modified stimuli and thus promote that even traces or consequences of gestures are enough to elicit embodied reactions and enforce the perceived authenticity of the artwork (Umilta et al., 2012; Sbriscia-Fioretti et al., 2013). Relating these findings to the similar reactions towards unauthentic art and AI art discussed above, we can translate these findings to our project. Even though we are not able to cover motor areas in our fNIRS montage, this research suggests different reactions to varying complexity and humanness (traces) of art – thus we investigate whether our varying stimulus complexity and the varying amount of human traces in our stimuli alters empathy activation.

However, these neural mechanisms are still not grasping all brain areas involved in aesthetic experiences. While we know reward-related areas of the brain activate even while preparing to view art, so far there is little empirical evidence for brain areas representing theories that identify empathic connection to the artist or perceiving intentionality as key components of art processing. Thus, this project aims to investigate these other possible anticipatory factors that might be activated in preparation of art appraisal.

2.7 Research Questions and Hypotheses

Reward-related areas of the brain activate while preparing to view art, especially in the context of original, gallery-labelled, human-made art (Kirk et al., 2008). In this present study we consider other regions or aspects of art experience that might also tie into anticipation of art. Since emotion communication and human connections seem to be crucial aspects of art processing, we argue that, aside from hedonic anticipation, people should prepare for empathic or social interaction before viewing art. Empathy and theory of mind areas of the brain might be activated when participants know that they are about to view art, comparable to the activation in reward regions that has already been studied.

Since we will look at the effects of different types of labels and different types of stimuli, we expect a differentiation of the amount of empathic anticipation in different conditions. We hypothesize that the activation will be stronger when participants expect to view human art than when they expect to view computer generated art. Since a section of computer-generated stimuli is based on a random pixel generator, there is no intention or emotional message behind these artworks. However, as previously discussed, due to the tendency to ascribe agency and intention to non-human artists, even these completely random stimuli might elicit empathic activation in their anticipation. The focus of this project lies on finding out whether there is empathy activation in anticipation of viewing art, and if this activation varies for different labels we provide.

Furthermore, as a second part of the study, we consider the discrepancy between the expectation of a certain kind of artist and the actual viewing of the stimulus. If an emotional connection between artist and viewer is essential for experiencing art, will contextual information about the “humanness” of the artist manipulate viewer’s opinions or will they be able to look through the framing and sense the art or humanness of the artist regardless of the label provided? We are interested in whether some participants might look through the priming and know that they are not looking at art by a human even though they were informed so. Or the other way around, participants might expect no or only little social interaction because of a computer prime, and then be surprised to find an empathic connection to an artwork that was in fact made by a human artist. Still another possibility is that even randomly computer generated pictures with a computer label might elicit empathy activation. That is why we will continue to monitor brain activity after the anticipation period, while participants view the art. Comparing these activation patterns will give us a more nuanced insight into the topic and will help to understand whether empathy activation will be adjusted according to the actual stimulus, depending on whether participants believe the priming or look through the label. Investigating these questions will provide an important addition to the empirical evidence surrounding the relationship between context, anticipation and empathy in art appraisal.

2.7.1 Hypotheses

1) People prepare for a social situation before viewing art. During this anticipation period, empathy areas of the brain will be activated in expectation before viewing art. This activation will be stronger in trials with a human prime than with a computer prime.

2) Empathy activation will change after actually seeing the stimulus: The activation will decrease if participants perceive the picture to be less likable and emotional than during viewing the label. The activation will increase if participants perceive the picture to be more likable and emotional than during viewing the label. For this change of activation, the label will be less important than the perceived humanness of the picture. Thus, people will be able to feel an empathic connection to a picture even though they believe that it has been computer generated.

3) For participants having a negative opinion on AI art, the differences between the priming conditions will be more pronounced than for participants without established opinion on the topic. Participants evaluate artworks made by a computer differently than artworks made by humans. Detecting the true nature of the stimulus through the prime influences the evaluation process and the aesthetic experience.

2.8 Neuronal Approach

2.8.1 fNIRS

The present study considers how empathy, perspective-taking and emotion contagion are associated with ambiguous computer generated and human-made digital art with varying labels. Previous studies have demonstrated that fNIRS is a strong tool to examine similar labelling concepts (Huang et al., 2011), and investigate brain areas associated with empathy and ToM (e.g., Liu et al., 2017, Hyde et al., 2018). Functional near infrared spectroscopy (fNIRS) is a technique for non-invasive brain imaging. Brain activity is measured through the flow of oxygenated and deoxygenated blood in monitored regions of the brain. Brain function is related to the hemodynamic response, which allows the inference of relative activation change in a certain area (e.g. Hoshi & Tamura, 1985; Rojiani et al., 2018). Light emitting and detecting optodes are placed on the desired areas of the scalp surface with a textile EEG cap. Through the emitter optodes, a signal of near infrared light is sent through and into the cortex, while detector optodes measure the light reflected. Since haemoglobin absorbs light, the detectors continuously measure changes in haemoglobin concentration through how much light is reflected in each region. Due to the utilization of near infrared light, this method can only monitor areas that are close to the cortical surface. While this may pose a limitation of the method, other factors make fNIRS an accessible and powerful method:

fNIRS has higher spatial resolution than for example EEG, while having the same depth-reach into the skull (e.g. Scholkmann et al., 2014). Moreover, fNIRS is robust against noise like movements of the participant, which makes it an ideal mobile tool. Experiments can even involve voluntary movement of the participant, and the results will still be reliable and correct. The information that can be inferred from fNIRS includes concentration change of oxyhaemoglobin, deoxyhaemoglobin and of total haemoglobin, which is more information about cortical blood oxygen metabolism than fMRI can provide (Scholkmann et al., 2014). fNIRS also has a higher temporal resolution than fMRI (e.g. Aarabi et al., 2017) and due to its lower cost and efficiency in comparison to fMRI, more participants can be tested. Another major advantage is its ability to provide experimental settings with high ecological validity (Kim et al., 2017). These benefits make fNIRS a reliable, affordable and valuable tool for studying emotion and social cognition

(Balconi & Molteni, 2016), which makes it a great method to use for the questions posed in this project.

2.8.2 Regions of Interest

Since this project focuses on areas associated with empathy and theory of mind, we monitored areas associated with these concepts. Since a NIRSport 2 was used for the present study, there are eight light emitting diodes for skin illumination and eight detectors placed on an EEG cap. These overall 16 optodes allow the monitoring of four different brain regions. After close consideration, the selected areas are the medial prefrontal cortex (mPFC), the left temporo-parietal junction (lTPJ), the right inferior frontal gyrus (rIFG) and the left lateral occipital area because they are most promising to yield the answers to the questions probed in this research project. In the following, we show the relevance and eligibility of each selected region for our purpose.

As described above, empathy, mentalizing and ToM are closely related. A network for mentalizing has been identified, represented by the temporal poles, mPFC and bilateral TPJ. These regions are typically engaged and are thought to interact during tasks requiring mentalizing and inferring others' mental states (Frith & Frith, 2006). The mPFC is associated with processes related to self-awareness and evaluating one's emotions. Introspection, self-reflection and social cognition are also related to this area (Krämer et al., 2010). In a meta-analysis, Seitz et al. (2006) suggests that mPFC mediates empathy. While mPFC activation has further been associated with self- and other-related judgements, abnormal patterns of mPFC activation have been associated with clinical disorders closely related to deficits in self-perception or deficits in understanding other people's beliefs, intentions or feelings (Denny et al., 2012). It has been argued that the PFC is connected to aesthetic appraisal, especially being active when viewing subjectively aesthetically pleasing images. This activation is assigned with the state of aesthetic focus rather than perception concerning features of the artwork (Cela-Conde et al., 2004, Jacobsen et al., 2005, Cattaneo et al., 2020).

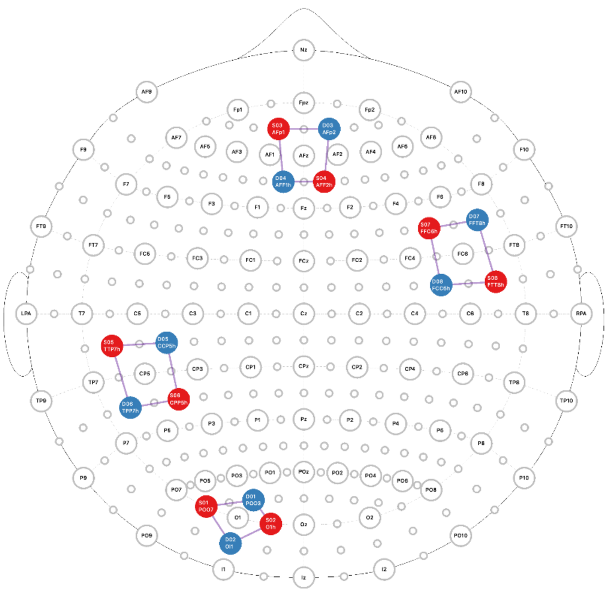
The TPJ plays an important role in theory of mind, perspective taking and cognitive empathy (e.g., Mai et al., 2016, Hyde et al., 2018). It is also connected to the processing of agency and intention (Jackson & Decety 2004). Disruption of the TPJ interferes with the ability to infer beliefs or intentions underlying actions (Young et al., 2010). Our focus lies on the left

TPJ, which is associated with inferring other's beliefs and intentions, and connecting mental ideas (Samson et al., 2004). The right IFG is linked to affective empathy and the feeling into emotions (Decety, 2010; review by Shamay-Tsoory, 2015). Jacobsen et al. (2005) investigated differences in brain responses when asking participants to look at patterns asking them to either judge its beauty or its symmetry. Participants showed higher activation in mPFC, IFG and TPJ in the aesthetic appreciation condition. Interpreting this activation, the authors mention that this task was introspective in the way that participants had to ask themselves whether the stimuli could be beautiful to them, therefore inferring from their own thoughts (Jacobsen et al., 2005). Moreover, Menninghaus et al. (2019) classify beauty or 'the feeling of beauty' as a class of aesthetic emotion. Distinguishing it from an objective beauty rating, the'feeling of beauty' is seen as a subjective feeling elicited by aesthetic virtue. This subjective aesthetic feeling and introspective process might build a connection to the picture, therefore classifying simple patterns as art with a human artist behind it and switching into an aesthetic state to look for intention and connection through the picture. This approach reinforces the importance of IFG and TPJ in art appraisal and why these regions are important to include to answer the questions posed.

Finally, for comparison, we included the left lateral occipital cortex. Past studies monitored this region to cover for visual attention without the focus on art appraisal (Kojima & Suzuki, 2010; Huang et al. 2011). The resulting optode montage is depicted in Figure 1. The red optodes are sources sending out infrared light, and the blue optodes are detectors that pick the light up again. Examining these regions will give us the best base to answer the research questions introduced.

Figure 1

Optode montage on the fNIRS cap



3. Method

3.1 Procedure

After conducting pilot trials during September 2021 where the process of the experiment was practiced and the montage on an fNIRS cap was prepared, data collection took place between the 27th of September and 4th of November 2021 in the fNIRS laboratory room in the faculty of psychology in Vienna. Due to Covid-19 experimenters and participants wore FFP2 masks during the greeting and explanations. After that, for easier fastening of the fNIRS cap and for the comfort of participants, participants were asked to remove the mask during the experiment. This was always agreed on beforehand by all people involved and was possible due to the applied 2G rule and the low infection rates during the period of testing.

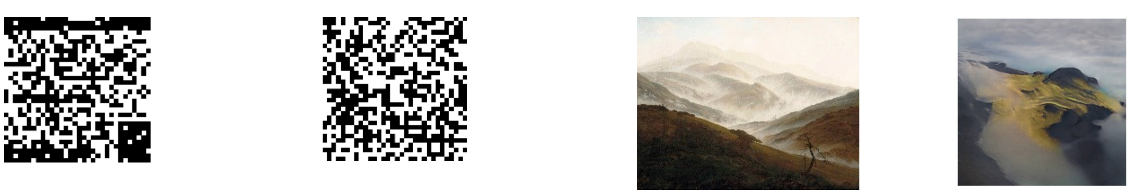
In total, the sample consisted of 40 participants, with 23 (57.5%) identifying as female, 17 (42.5%) identifying as male and no participants identifying as other or declining to answer. The sample included people studying or employed in various fields, thus making the sample diverse in age and field of profession. The mean age of participants was M = 35 (SD = 15.4), ranging from 21 to 68 years. The educational background was not as varied, as most participants had a bachelor's degree (25, 55.56%) or a master's degree (12, 26.67%) and 8 people (17.78%) had completed the A-levels. Participants were recruited through communication, social media and the LABS system. The psychology students recruited via the LABS system received 4 credits for the participation and completion of the study. However, none of the participants received payment or another reward for the participation or completion of the study. Due to technical reasons or unusable data, 5 participants had to be excluded from the starting sample, therefore resulting in the sample of 40 participants who finished both the behavioural and the neuronal part of the study.

3.2 Material

The visual material consisted of four different kinds of stimuli – digital art made by human artists, highly similar computer generated digital art, representational art and art that was created using a GAN and CAN software. These categories allowed us to gain detailed insight into the process and the mechanisms that occur during art appraisal – both from digital and representational art and with varying amounts of influence of a human artist in the AI and computer generated paintings. Moreover, using other stimuli than only highly similar simplified digital art ensured that the participants would not get fatigued throughout the study and stay alert and susceptible for the labelling used. A selective overview of the stimulus types can be seen in Figure 2. All images used in the study are depicted in Table 1.

Figure 2

Overview of stimuli categories



Digital art made by human artist	Randomly computer generated digital art	Representational landscape paintings	AI Art

3.2.1 Digital Art

Two categories contain digitally produced stimuli, digital art created by human artists and computer generated digital art. For the categories to be as similar as possible, the formal parameters and rules were carefully selected and were applied to both human and computer generated images.

Figure 3

Inspiration for the digitally created stimuli

G. Richter – 4900 Farben (2007)
Source: Richter (2007)

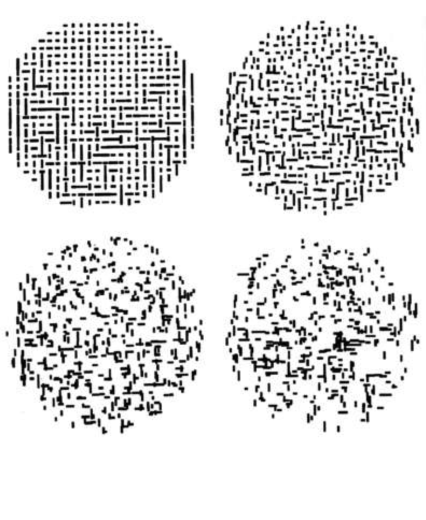
G. Nees – Plastik 1 (1966-1968)
Source: Herzogenrath et al. (2007)

On the one hand, the digital art for this study was selected to satisfyingly represent and be considered art. Taking inspiration from artworks like Gerhard Richter's '4900 Farben', his colour charts and early computer generated art like Georg Nees' 'Plastik 1' for the scheme of the stimuli assured this (Figure 3). On the other hand, the digital art should be reduced and simple. Therefore, it was decided to keep the colour scheme to black and white. Moreover, a unified grid of 32x32 squares (14,17 x 14,17 pixel per square) was provided for each picture, resulting in a 16x16 cm (453.5 x 453 pixel) square in total. Each square unit could individually be coloured either black or white. A group of nine visual artists (6 female, 3 male) was hired to create the stimuli set for the human art. Each artist was asked to create individual images by colouring the squares in a prepared template in Illustrator (Adobe Inc., 2019a, 2019b, 2019c) with the intention of creating an abstract artwork that would convey one emotion the artists felt during the creation process to the viewers. All of the artists' digital work were created for and used in a previous behavioural study examining emotional transmission in highly similar computer generated and human-made digital art (Demmer 2021). Even though the original set of these artworks consists of 14 pictures, we reduced the number of stimuli to eight to facilitate the completion of the study and adapt to the higher number of picture categories and the inconvenience or discomfort participants might feel during a long session with fNIRS.

For the highly similar looking computer generated digital stimuli, a random noise generator (RNG) (PINETOOLS, n.d.) created a random pattern for each picture by filling the cells black or white randomly. For four of the eight pictures, the ratio of black and white squares was set to be equal. The remaining four stimuli were added after analysing the pictures made by the human artists. Since some artists coloured the squares mostly white, after careful consideration we decided to add pictures with a higher ratio of white in order to keep similarity of both stimuli sets. Thus, one stimuli with a ratio of 60% white squares, one with 65% and two with 70% of white squares were created with the same random noise generator. Overall, the final digital stimuli set consisted of 16 pictures, eight computer generated pictures and eight made by human artists. The combined digital stimuli set reminds of Michael Noll's project in 1964 where he paired a black and white version of the Mondrian painting 'Composition with Lines' (1917) consisting of geometrical shapes with a similarly composed "semi-random" (Noll, 1966) computer generated picture ('Computer Composition with Lines') (Figure 4). Noll's project included a questionnaire, where only about quarter of the participants were able to identify which picture was the original and almost two thirds of participants preferred the computer generated version (Manovich & Arielli, 2022). These results suggest that the pairing of reduced black and white geometric pictures made by human artists and highly similar computer generated versions is a promising foundation for the present experiment.

Figure 4

Michael Noll (1964): 'Computer Composition with Lines'. Source: Noll (1964)



Moreover, as mentioned above, we decided to add two more stimuli categories, representational landscape art by renowned artists and AI art that was created using a GAN and a CAN software, respectively.

3.2.2. Representational and Generative Stimuli

The representational images were picked from the Vienna Art Picture System (VAPS), which is a database initiated to facilitate the access to art in aesthetic research (Fekete et al., 2022). It includes copious pictures by renowned artists from various periods throughout art history. For this study, we selected landscape art with idealistic, impressionistic, post-impressionistic, and expressionistic tendencies. It was important to strictly exclude any pictures with living beings or objects that were reminders of human culture, like houses, boats or fences. Moreover, the artworks should not be immediately recognizable as famous pieces of art. These criteria resulted in a set of eight landscape pieces from different periods of time created by different artists in varying styles. A full list of the stimuli can be found in the appendix (Table 12).

Corresponding to the landscape artworks, most of the generative AI art was selected from work resembling realistic landscape art by the collective Obvious. Obvious provides art that was made with a Generative Adversarial Network (GAN). GAN is a machine learning tool that utilizes a given training set of images to generate completely new data with the same statistics as the training set. The network consists of two networks. The generator creates images that match the data from the training set as closely as possible, while the discriminator constantly tries to discern the fake data provided by the generator from the real data of the training set. While doing so, it provides feedback to the generator, which then updates its strategy to assimilate to the real data. Only when the discriminator is not able to distinguish between training set and new data, the credibility of the new data is high enough and satisfying images can be produced. (Goodfellow et al., 2014) Four stimuli for the present study were taken from the project 'Energy of the Earth. Amplified.', in which the group Obvious collaborated with the artist Stas Bartnikas to provide a certain training set to be given to the AI, resulting in landscape-inspired pictures mostly showing mountains against the sky.

As mentioned in the literature review, the discussion about the human influence in generative art made with an AI program is ongoing. Thus, we decided to balance the GAN stimuli with four pictures made with a Creative Adversarial Network (CAN). CAN is an advancement of the GAN principle in the sense that while also creating art, it focuses on the art experience and on newness and creativity in regards to art style and norms while keeping to the framework, meaning the picture produced has to be classified as art but cannot be attributed to one specific art style. This increases the chances of arousal and emotional transmission on the viewer's side. This result can be achieved by adapting the role of the discriminator. Like GAN, CAN consists of a generator and a discriminator. The discriminator is provided with a training set of classified art and gives twofold feedback to the generator: On the one hand, it assesses whether the picture can be placed within the training set, therefore being considered art. On the other hand, it provides information about the art style of the picture, the goal being to create an image outside of a specific art style (Elgammal et al., 2017). To the date of conducting the study, the most accessible fitting and authentic CAN images were the ones created by Ahmend Elgammal and his team in their original project introducing CAN networks to the scientific community (Elgammal et al., 2017). However, our team was not able to complete the conversation with the authors to gain access to high resolution images of four well-fitting images shown in the paper. Since the use of CAN pictures was an important chance to introduce varying degrees of human authorship in generative stimuli, we used lower resolution versions of four pictures vaguely representing abstract landscapes and therefore fitting with our theme of stimuli. This resulted in a set of generative stimuli consisting of four pictures created with a GAN and four images created with a CAN.

Taken together, the study uses 32 stimuli that can be divided in four categories, each consisting of eight stimuli.

3.3 Experimental Set Up

3.3.1 Pilot Study

In the main part of our study, a balanced stimuli set is essential to avoid grouping effects. To ensure this, we conducted an online pilot study using Qualtrics (Qualtrics, Provo, UT). All 28 originally digitally produced stimuli were presented on the screen in random order to 35 participants. The mean age of participants was M = 30.6 (SD = 6.4), ranging from 22 to 57 years. 22 (62,9%) participants identified as female, and 13 (37,1%) participants identified as male. Participants were asked to decide for each picture whether it was made by a human artist or whether it was computer generated. For each picture, the mean rating, standard deviation and the answer given most often were calculated. The data was analysed statistically and visually. The pictures were ordered from largest to smallest mean value. To avoid grouping effects and to ensure a similar susceptibility for the labelling used in the main study, the most extreme ratings (highest and lowest) were divided into the two groups separately. After that, all similar in-between ratings were also divided between the two groups in a balanced way. For ecological reasons, two balanced sets of four digital artworks by human artists each and two balanced sets of four computer generated pictures each were selected for the study.

For the stimuli previously used in Demmer (2021), a pilot study had been conducted as well in that experiment. Comparing the present results with the former results, the ratings were consistent with the groups ultimately consisting of the same stimuli. The final stimuli sets are depicted in Table 1.

3.3.2 Pre-Questionnaire

To answer the research questions of this project, we asked each participant to fill out a questionnaire four to seven days before the main part of the study takes place. The timely distance to the main part was to prevent influencing participants' reaction to the labelling and the stimuli. In this questionnaire, we generated a participant code to match this data with the main study. The questionnaire collected information about the participant's opinion on and experience with AI art in general, authorship in AI art, openness to the concept of emotion transmission in art and previous art experience in general. As control variables, opinions on and experience with art fakes and art made by children and animals were included. Moreover, the questionnaire included the Questionnaire of Cognitive and Affective Empathy (QCAE), a questionnaire analysing the trait empathy of each participant (Reniers et al., 2011) which has been used in studies in similar fields or with similar goals (Pelowski et al., 2018, Kühnapfel, 2020). The questionnaire consists of 31 items monitoring 5 sub-factors of cognitive and affective empathy. 'Emotion contagion' (mirroring feelings of others automatically) and 'Perspective taking' (intuitively taking another person's perspective to gain cognitive insight into another viewpoint) represent cognitive empathy. Affective empathy consists of the factors 'Online stimulation' (gaining insight into other's feelings by imagining oneself in the other's position), 'Proximal responsivity' (noticing and sympathizing with the mood of others in a close social context) and

‘Peripheral responsivity’ (taking on a detached position when viewing emotion, similar to the state of ’aesthetic focus’) (Reniers et al., 2011).

3.3.3 Main Study

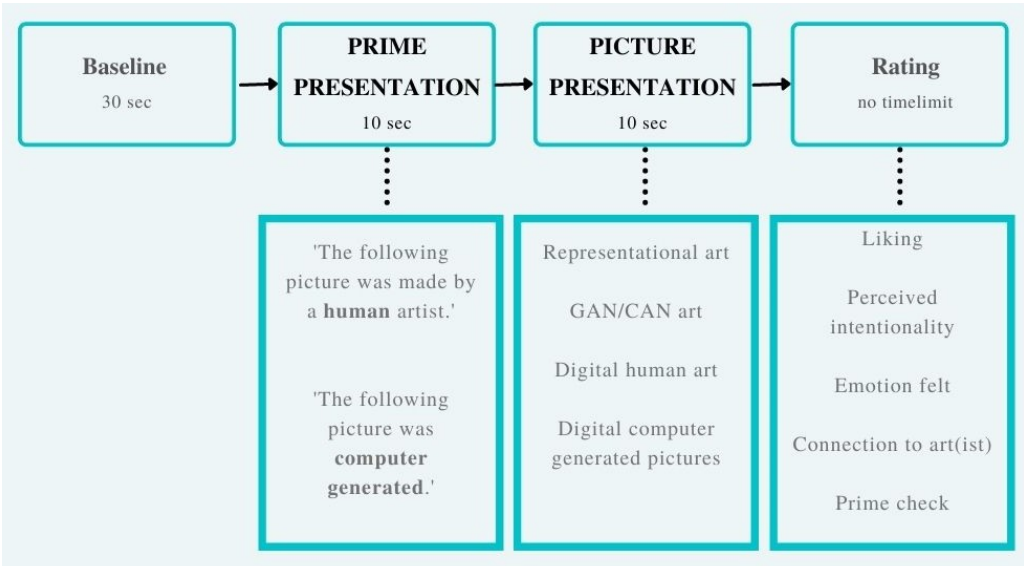
About three to seven days after completing the first part of the study online, participants were invited to the fNIRS laboratory room in the faculty of Psychology, where they took part in the main experiment, a prime-picture-rating task while collecting fNIRS and behavioural data.

Figure 5 illustrates the basic process of the experiment. After a brief greeting and explanation of the study, the fNIRS cap is attached to the participant’s head and the appliance is synchronized in order to collect data from the correct brain regions. After general instructions appearing on screen, each participant is first instructed to relax in front of the screen for 30 seconds, which provides us with a baseline brain activity of each person. The baseline screen is black and reads “Please relax now”. Then, each subject views the label for 10 seconds, which allows us to gain data to answer the question which differences the anticipation of human art vs. computer generated art will show in the monitored brain regions. After that, the corresponding picture is also viewed for 10 seconds. Then, the participant will rate each picture on how much they liked it, whether they could pick up an intention of the artwork, if they felt emotion during viewing the picture, if they felt a connection to the artwork or the artist through the picture and how much the picture seemed human made or computer generated - depending on which label the picture was paired with.

The fNIRS data was acquired with a NIRSport2 device using Aurora acquisition software (NIRx Medical Technologies LLC) at near infrared light wavelengths of 760 and 850 nm and signals were recorded with a sampling rate of approximately 10.17 Hz.

Figure 5

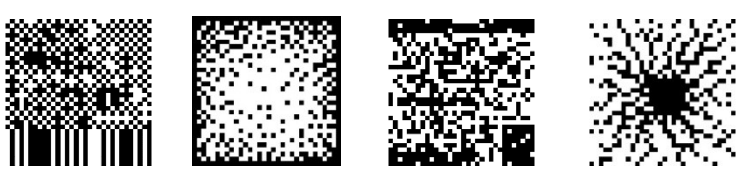
Visual set-up of the experiment procedure

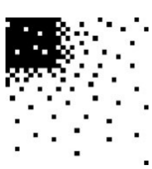
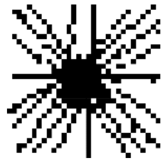
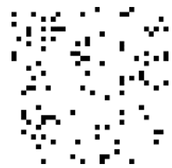
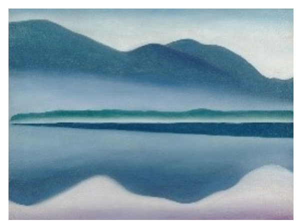
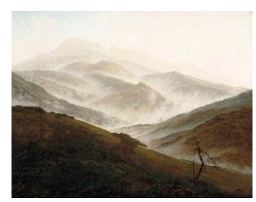
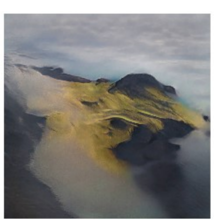
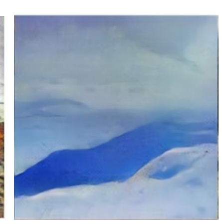


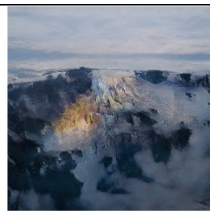
To avoid grouping effects, each category of stimuli was divided into two groups. Each group or version contains all 32 stimuli, but the labels were contrary in each version. Half of the participants received Version A of the study and the other half received Version B. Table 1 shows Version A with all 32 stimuli. For Version B, the stimuli groups and the pictures stayed the same, with only the label being reversed. Thus, the matching of prime and picture was not random, but each prime-picture-pair was fixed for each version and trial. Every person saw every picture with its corresponding label, according to the experiment version. Participants with an odd number of participating were provided with Version A, participants with an even number of participating were provided with Version B.

Table 1

Corresponding Primes and Pictures used in Version A

Prime	Picture (full list of pieces and artists in appendix Table 12)
human	Pixel art made by human artists 

computer generated	Pixel art made by human artists    
human	Randomly computer generated pixel pictures    
computer generated	Randomly computer generated pixel pictures    
human	Representative art    
computer generated	Representative art    
human	AI art GAN GAN CAN CAN    
computer generated	AI art GAN GAN CAN CAN

Note. This table shows the full stimuli set of Version A. All pictures are listed with the prime they were paired with. The pictures were the same in Version B, however the primes were opposite.

For each participant, the first trial was a test trial showing the human label and then the Mona Lisa (Da Vinci, 1503/1519) to ensure that each participant understood the procedure of the following trials and to answer any questions regarding the questionnaire or the process without disturbing the real trials. After much reflection, we decided to settle for a semi-random presentation order of the prime-picture pairs. The first four trials were fixed and were the same for each participant in Version A and Version B, respectively. For these trials, we selected one pair of each picture category with a truthful prime. The digital pictures with the highest hit rates in the pre-study were selected for these trials. This way, participants stayed more unsuspecting of the labels and got to know each category. After those four fixed trials, the presentation order of the remaining 28 trials was random.

3.3.4 Post-Questionnaire

After completing the main part of the experiment, participants were asked to fill out a short questionnaire collecting demographic data and reflecting on thinking or rating patterns concerning the stimuli and labels. This way, we were able to collect information on the participants' opinions on the pictures, focussing on the pixel pictures, on participants' apprehension of the labels used and whether they applied certain strategies when rating each picture.

Afterwards, participants were able to ask any questions they had, either regarding the method used, the experiment and its purpose or anything else related to the present study. Right before leaving, we thanked the participants and offered them chocolate. No other form of reward was given before or after the experiment.

4. Results

4.1 Pre-questionnaire

We summarized the results of the QCAE. A descriptive overview is listed in Table 2.

Table 2

QCAE results of the pre-questionnaire

Measure	N	M	SD	Range
Female	24			
Male	18			
Age	42	34.9	15.27	[21-68]
High school	6			
Apprenticeship	1			
Bachelor	23			
master	12			
C-OS	42	4.8	0.77	[2.5-6.6]
C-PT	42	5.1	0.69	[3.6-6.5]
A-EC	42	4.6	1.18	[1.4-6.6]
A-PrR	42	5.1	1.09	[1.9-6.8]
A-PeR	42	4.5	1.08	[1.6-5.9]

Note. N represents sample size, M and SD represent mean and standard deviation, respectively. C-OS = Cognitive Empathy - Online Simulation, C-PT = Cognitive Empathy - Perspective Taking, C-EC = Affective Empathy - Emotion Contagion, A-EC = Affective Empathy, APrP = Proximal Responsitivity, A - PeR = Affective Empathy - Peripheral Responsitivity

Moreover, we grouped the statements from the pre-study into five variables: previous knowledge and information about AI art, opinions about authorship of AI art, beliefs about emotion transmission by both human and AI art, previous art experience and a control variable asking opinions about art fakes and art made by children or animals. An overview of these self-ratings is listed in Table 3.

Table 3

Descriptive overview of participants' opinions prior to the main study

Measure	N	M	SD	Range
Previous knowledge about AI art	42	3.3	1.3	[0.8-5.6]
Benevolent opinion about authorship of AI art	42	3.7	1.9	[0.5-6.8]
Openness to emotion transmission by both human and AI art	42	4.2	1.6	[0-7]
Previous experience with art	42	3.4	2.7	[0-7]
Opinion about forged art and art made by children or animals	42	4.0	1.1	[1.5-6.5]

Note. N represents sample size, M and SD represent mean and standard deviation.

4.2 Post-questionnaire

From overall 45 people participating in the fNIRS experiment, 17 people stated that they believed all label categories equally. When asked about the different labels, 22 participants did not always believe the labels for pixel pictures, with 10 people not always believing the label "human" when pixel pictures appeared. Six participants did not always believe the label "computer generated" when pictures seemed to have obvious patterns to them. Generally, 18 people did not believe the label "human" when the pictures were not clear while six people did not believe the label "computer generated" when the pictures had clear shapes or contours. Seven people stated to have hardly paid attention to the labels. 11 participants claimed to have known one or more of the artworks shown. Overall, most people believed the labels fully or partially, which is important for our research questions regarding solely the expectation period. Thus, in the analysis, brain imaging data from participants who claimed to have not believed the labels or tried to ignore them were excluded for analyses concerning the expectation period.

Next, participants were asked to recall the pixel pictures and answer questions about the ratings and thinking patterns regarding these stimuli. These ratings and all answers to the two open-format questions in the questionnaire are listed in the appendix (Table 10 and 11).

4.3 Main Study

All statistical analyses were conducted using the software IBM SPSS 27 and R-4.1.3. Before doing any statistical analysis, we compared the data from version A and version B. There was no significant difference between the two versions, thus enabling us to treat the two experiment versions as equal and combining them. Datapoints from participants who claimed to have ignored the labels or not believed them at all were removed for the analyses concerning the data during viewing the prime.

4.3.1 Behavioural data

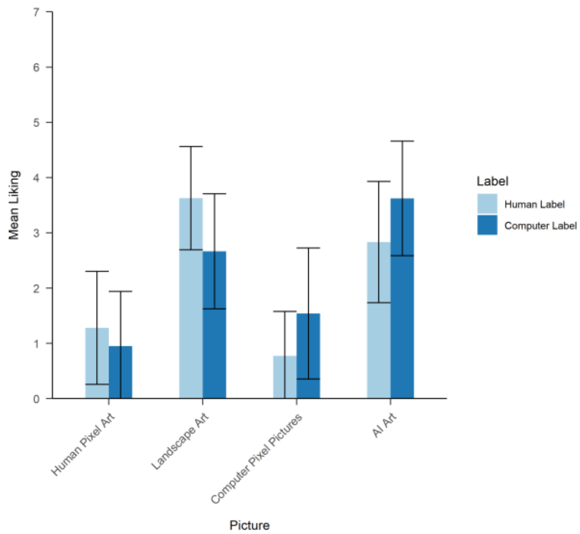
We wanted to investigate whether the prime or picture showed a relation to people's behavioural ratings (liking, sensing intention, feeling emotion, feeling connection). To answer this question, we looked at the reported ratings for each of the overall eight prime/picture type combinations.

Figure 6 a-d shows the average ratings over all participants for each prime/picture category. The bars represent mean feelings over all participants, with error bars marking the standard deviation. Generally, both pixel picture categories (human-made and computer generated) received lower ratings than both representative and more visually complex categories (landscape art by renowned artists and AI art). Looking at these category pairs separately, we see that the human made art usually elicited higher ratings of the variables (liking, emotion, connection and intention) than the computer generated counterpart, regardless of the prime.

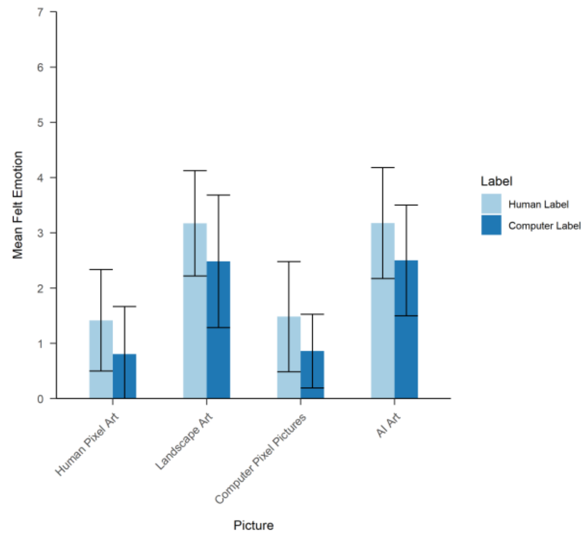
Figure 6 a-d

Mean ratings of liking, felt emotion, felt connection and perceived intention of each prime and picture type

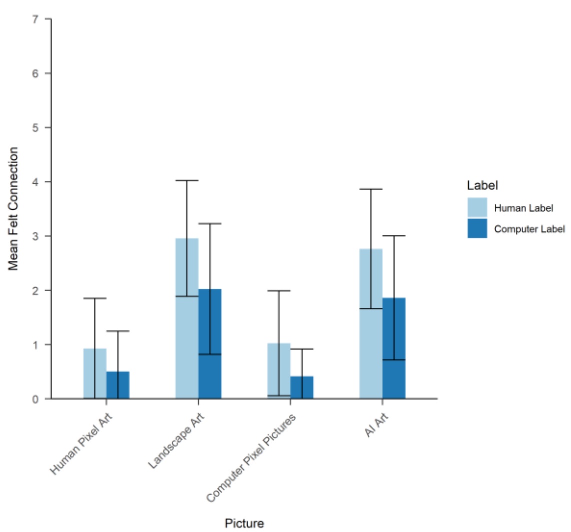
a) Liking



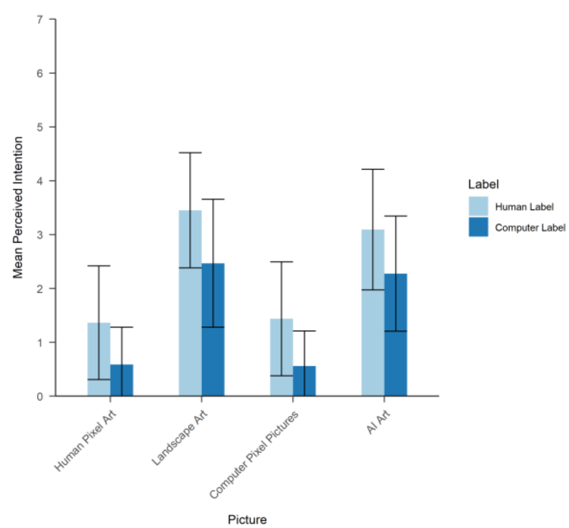
b) Emotion



c) Connection



d) Intention

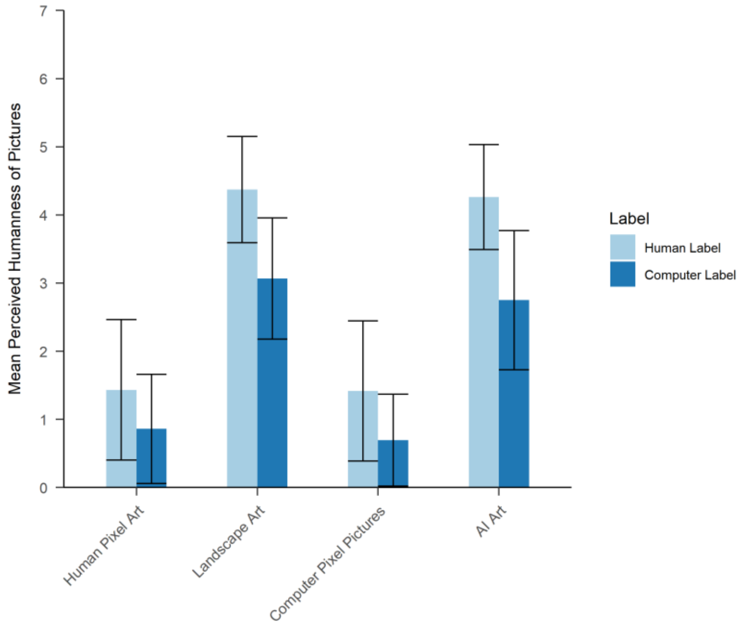


How human and computer generated was each category rated?

As for people’s beliefs concerning the nature of the picture (humanmade or computer generated), Figure 7 shows the mean ratings for this question. People were asked after each picture to rate it on a scale from zero (computer generated) to seven (made by a human). The mean ratings for each picture category with both labels are depicted in Figure 7.

Figure 7

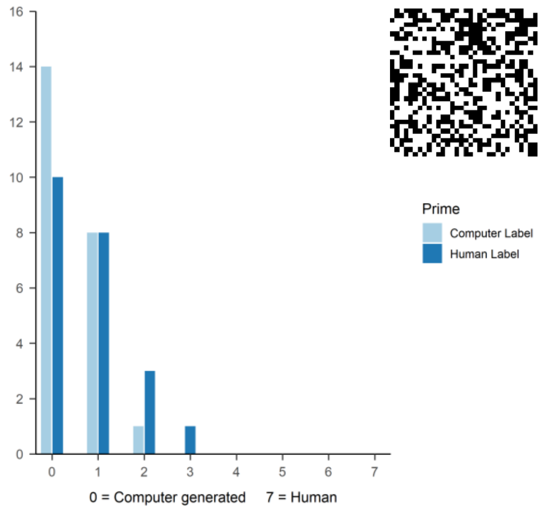
Mean humanness ratings of each picture category, grouped by the label provided



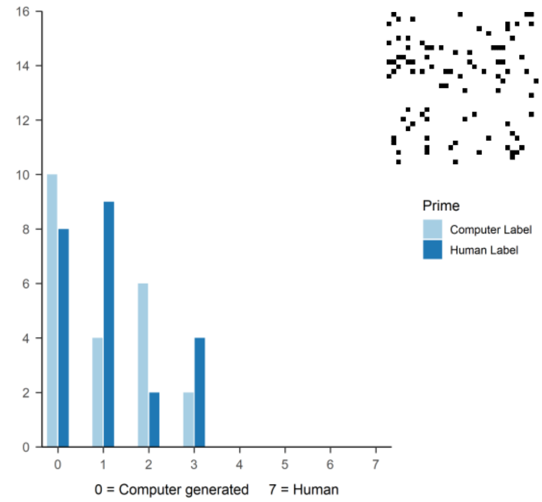
We wanted to accentuate the humanness ratings of the randomly computer generated pixel pictures, since we are interested in whether these pictures were estimated to be completely computer generated or whether people tended to find humanness even in these randomly generated pictures. Humanness ratings were similar for all pictures, only the pictures with a higher white percentage eliciting a little bit more "human" rates than the completely balanced ones. The prime did not alter the humanness ratings for each picture by much. Figure 8a-h illustrates these ratings. While there was no picture judged only with the lowest rating (indicating no sensed humanness at all), only for very few pictures (8d, e and f) there were ratings that leaned towards the "human" side of the scale.

Figure 8 a-h

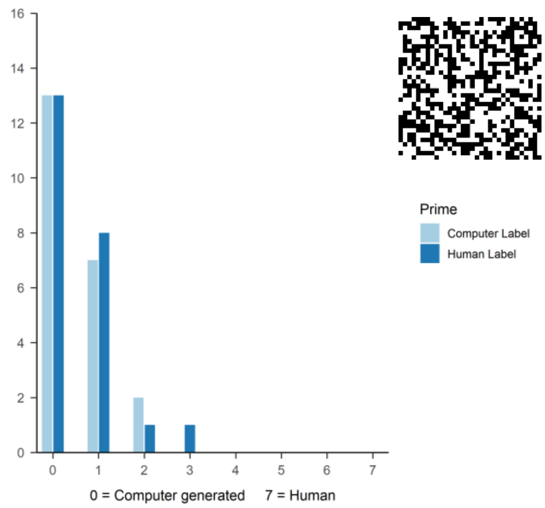
Mean Humanness Ratings of each computer generated pixel picture



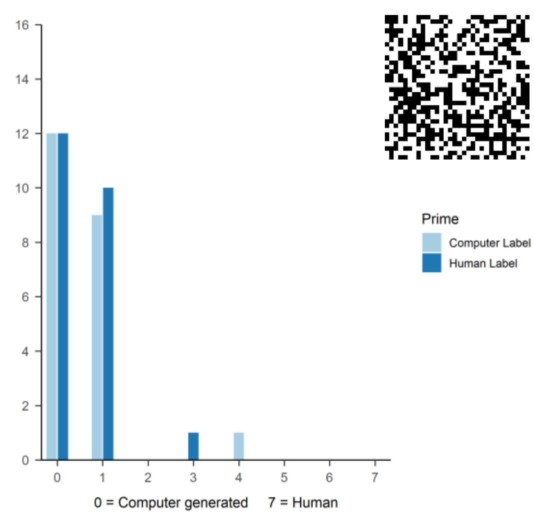
a)



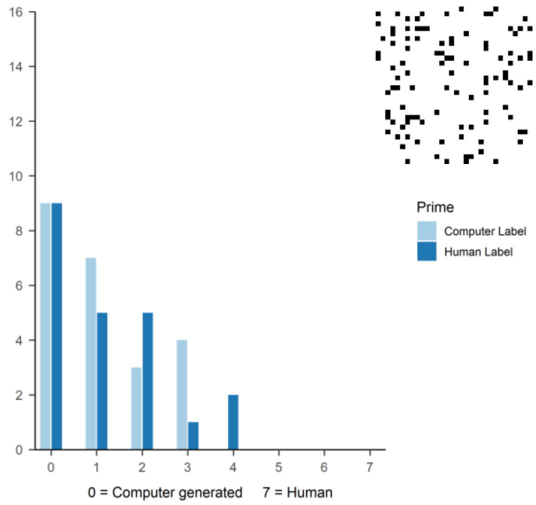
b)



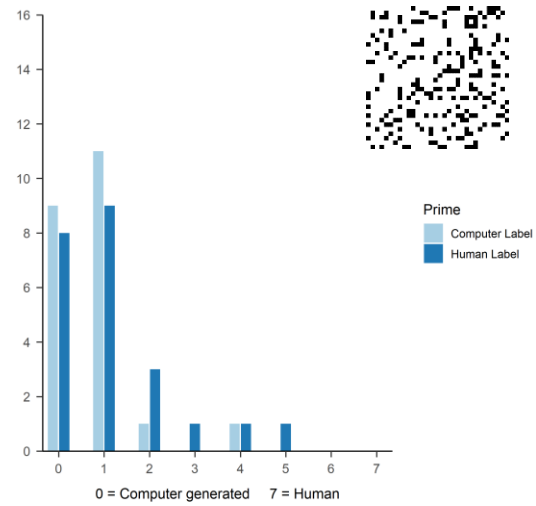
c)



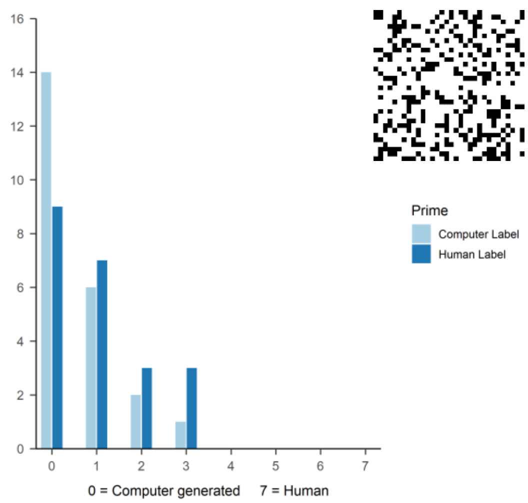
d)



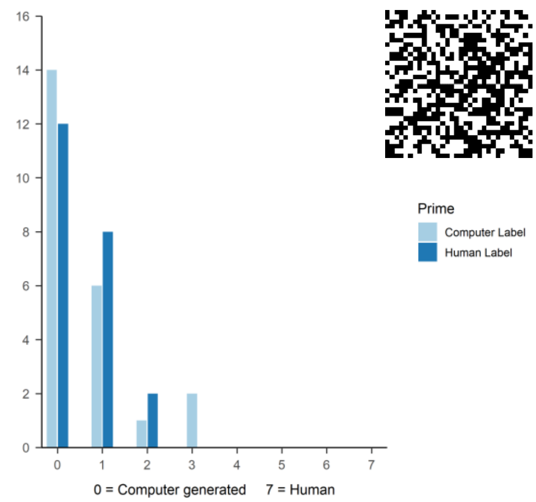
e)



f)



g)

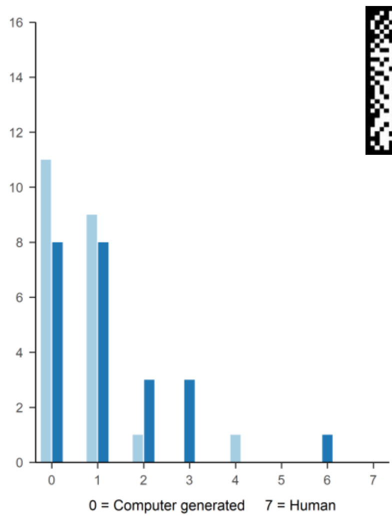


h)

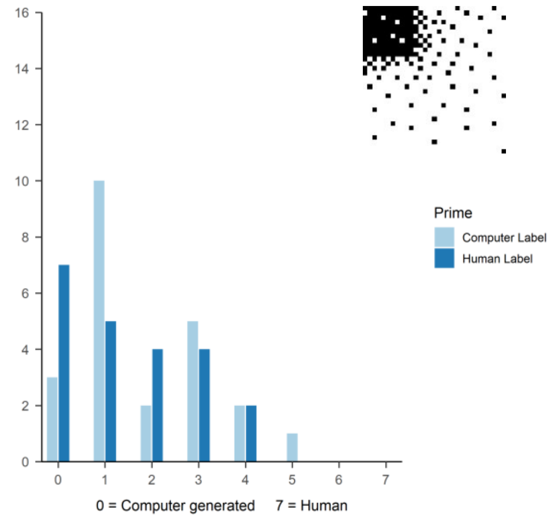
To compare the humanness ratings of the computer generated pixel pictures to the ratings of the pixel pictures provided by artists, the mean humanness ratings for the latter are depicted in Figure 9a-h. For these pictures, there were more ratings on the "human" side of the scale (4-7) than for the randomly computer generated ones, which shows that the pictures made by human artists are rated as being more "human" than the randomly computer generated pictures, regardless of the label provided.

Figure 9 a-h

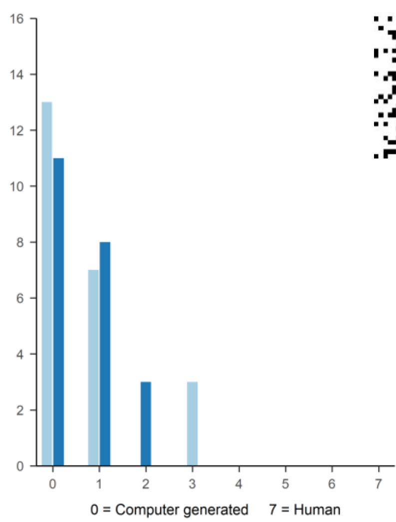
Mean Humanness Ratings of each pixel picture provided by human artists



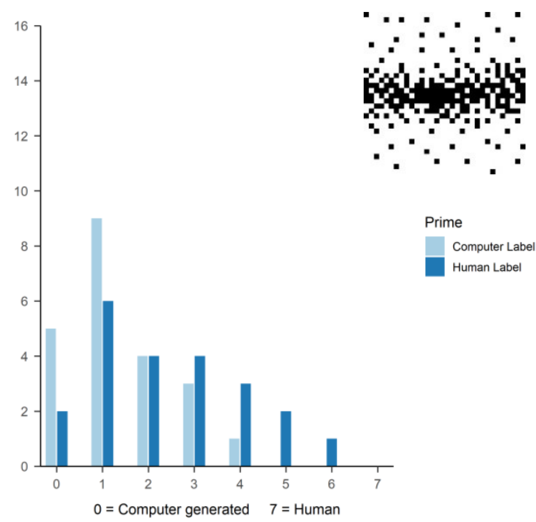
a)



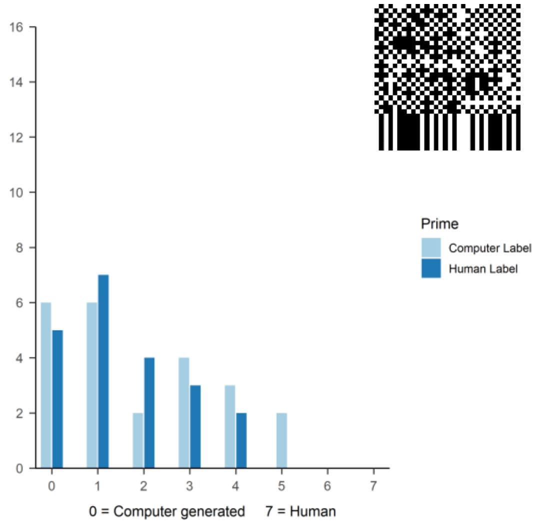
b)



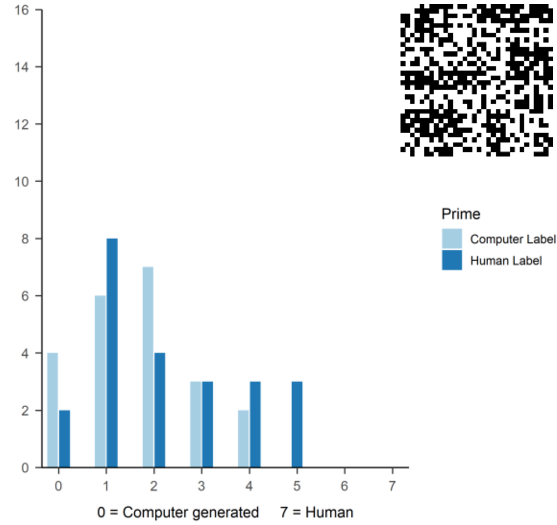
c)



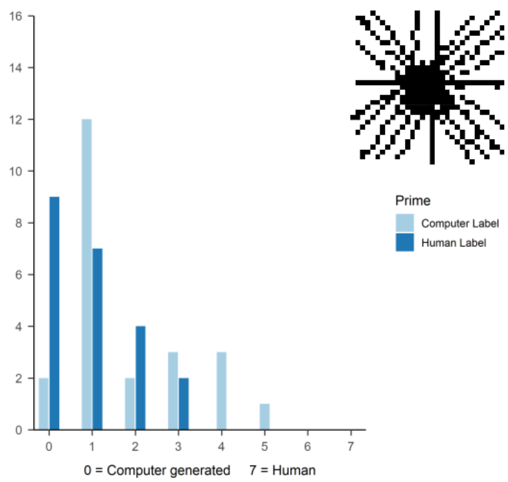
d)



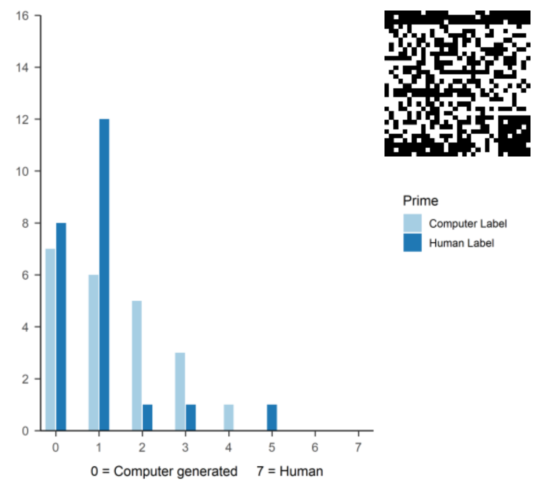
e)



f)



g)



h)

Does the prime or the picture influence people's ratings more?

For each behavioural variable, we calculated a two-way repeated measures ANOVA to examine whether there is a main effect of the prime or of the picture category or whether there is an interaction between the prime and the picture. We tested for a main effect of prime and picture within subjects between all conditions for liking, felt emotion, felt connection and perceived intention. The data was not normally distributed. However, since ANOVA is a robust tool, we decided to continue with the analysis (Wilcox, 2012).

Liking

For Picture, the Huynh-Feldt adjustment was used to correct for violations of sphericity. We found a significant main effect for Picture (*F* (2.53, 111.47) = 161.12, $p < .001$, *pη2* = .785), with Picture explaining 78.5% of the variance, but not for prime (*F* (1,44) = 1.95, $p = .169$, *pη2* = .043) or the prime-picture interaction (*F* (2.97,160.65) = 4.04, $p = .009$, *pη2* = .084). (Figure 10a)

Intention

We found a significant main effect for Picture (*F* (3, 132) = 173.97, $p < .001$, *pη2* = .798), with Picture explaining 79.8% of the variance, but not for prime (*F* (1,44) = 4.07, $p = .05$, *pη2* = .085) or the prime-picture interaction (*F* (2.8,26.4) = 4.04, $p = .011$, *pη2* = .084). For the interaction prime*picture, the Huynh-Feldt adjustment was used to correct for violations of sphericity. (Figure 10b)

Emotion

For Picture and the Prime*picture interaction, the Huynh-Feldt adjustment was used to correct for violations of sphericity. We found a significant main effect for Picture (*F* (2.72, 119.54) = 155.21, $p < .001$, *pη2* = .779), with Picture explaining 77.9% of the variance, but not for prime (*F* (1,44) = .485, $p = .490$, *pη2* = .011) or the prime-picture interaction (*F* (2.78,122.33) = .093, $p = .956$, *pη2* = .002). (Figure 10c)

Connection

For both Picture and Prime*Picture interaction, the Huynh-Feldt adjustment was used to correct for violations of sphericity. We found a significant main effect for Picture (*F* (2.64, 115.98) = 128.44, $p < .001$, *pη2* = .745), with Picture explaining 74.5% of the variance, but not for prime (*F* (1,44) = 1.95, $p = .170$, *pη2* = .042) or the prime-picture interaction (*F* (2.68,117.82) = 1.905, $p = .139$, *pη2* = .042). (Figure 10d)

Even though there was no significant effect of the prime on people's ratings, the graphs show a certain trend that in all categories except for the liking ratings of computer pixel pictures and AI art, pictures with the human prime received higher ratings in liking, felt connection, perceived intention and felt emotion than pictures with the computer prime.

Figure 10a

Interaction: Mean Liking Rating per Picture Category, grouped by Prime

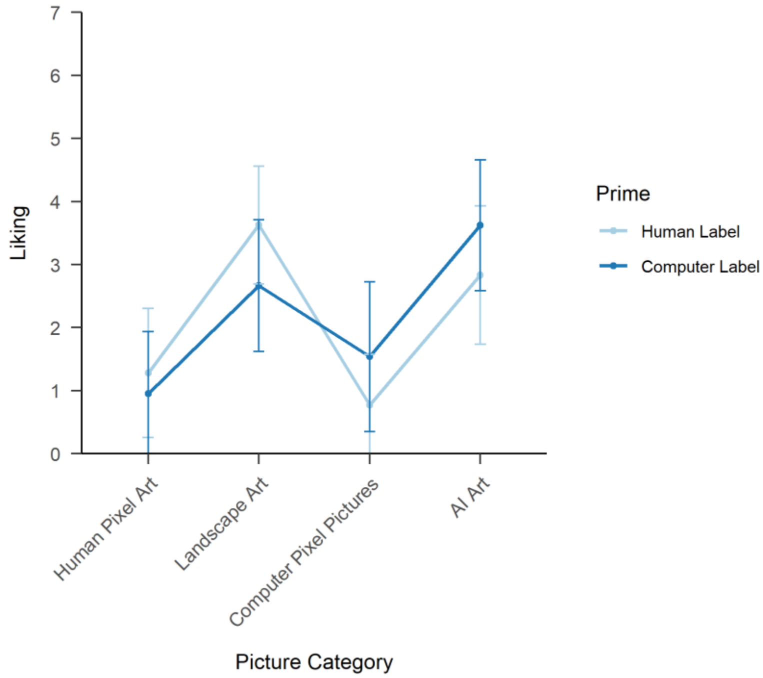


Figure 10b

Interaction: Mean Perceived Intention per Picture Category, grouped by Prime

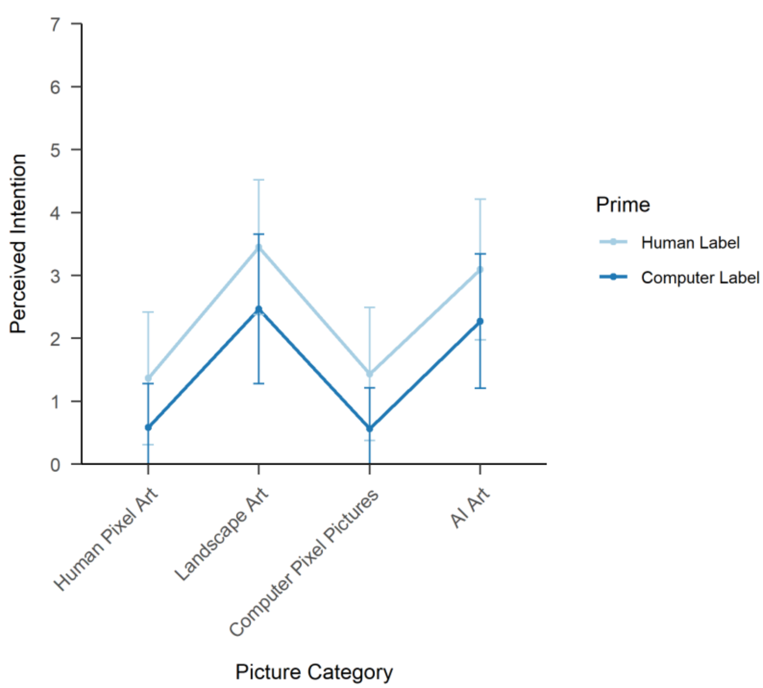


Figure 10c

Interaction: Mean Felt Emotion per Picture Category, grouped by Prime

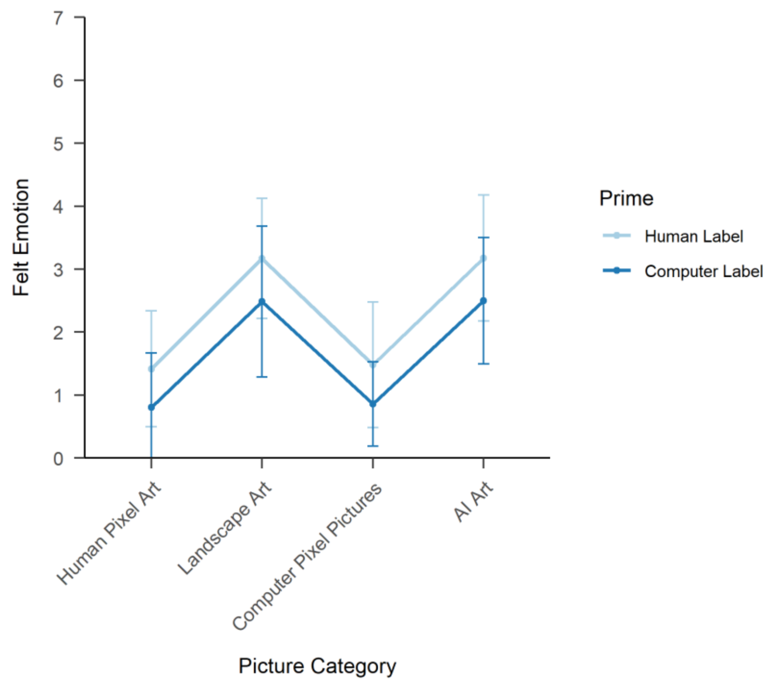
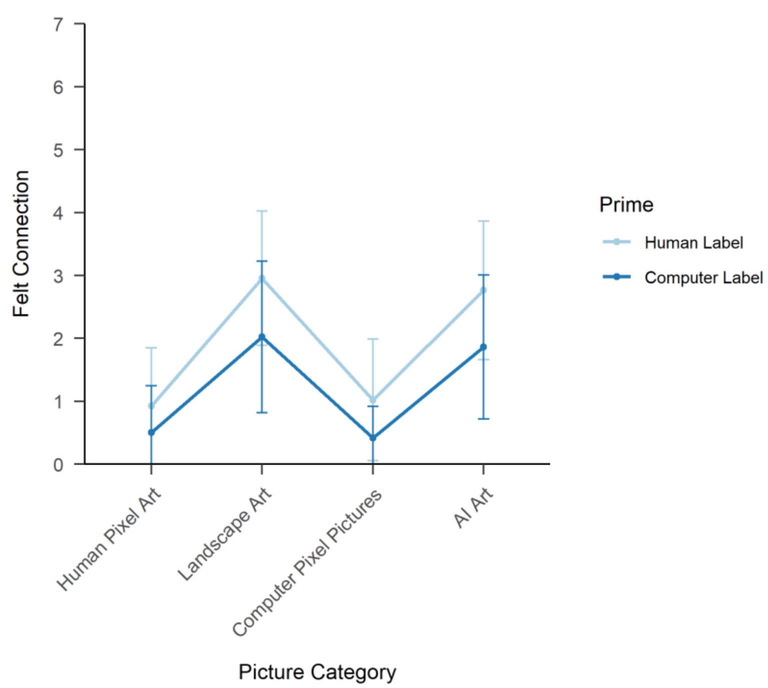


Figure 10d

Interaction: Mean Felt Connection per Picture Category, grouped by Prime



4.3.2 fNIRS Data

Data preprocessing

The raw data was preprocessed in Matlab 2021b (MATLAB and Statistics Toolbox Release 2012b, The MathWorks, Inc., Natick, MA, USA), using the HOMER3 toolbox (Huppert et al., 2009). NAN were intrapolated automatically by Aurora. Then, data preprocessing followed established steps: Channels with insufficient signal or data were checked visually using lineplots and CWT plots. Then, channels were pruned according to a predefined filter by Homer3 with a datarange of [0.3 – 2.5] and a signal-to-noise-ratio threshold of 10. After that, the wavelength data was converted to optical density. Then, motion artefacts were identified and corrected with spline interpolation. Then, a band-pass filter [0.2 – 0.01 Hz] was applied to suppress physiological oscillations. Finally, the changes in optical density were converted to relative changes in concentrations, resulting in HbO^2 (oxygenated hemoglobin), HbR (deoxygenated hemoglobin) and HbT (total hemoglobin) data according to the modified Beer-Lambert law. For this, differential path length factors of 7.3 for wavelengths of 760 nm and 6.4 for wavelengths of 850 nm were applied. After exporting, the data was Z-scored by subtracting the mean of baseline activation and dividing by the standard deviation to ensure commensurability for all participants' data. Outliers were removed according to the Inter-Quartile-Range Method.

Difference in brain activity during baseline and during viewing the label

Before answering the research questions, we examined the brain activity difference between the baseline activity and the activity measured during viewing the label to see whether viewing the labels elicited a different activity than viewing the baseline screen. For this, we conducted t-Tests to analyze the difference between the baseline activation and the prime-viewing data of each ROI. There was a significant difference of brain activity between the baseline and the viewing of the label for mPFC, lTPJ and O1 (Table 4), with the activity during the baseline being higher than the activity during viewing the label.

Table 4

T tests between baseline activity and activity during viewing the labels

		M	SD	t	df	p
mPFC	Baseline	-.31	.72	-2.12	54.1	.03
	Label	-.58	1.54			
lTPJ	Baseline	-.34	.87	-2.14	48.9	.03
	Label	-.63	1.42			
rIFG	Baseline	-.18	.95	-1.83	48	.07
	Label	-.47	1.57			
O1	Baseline	-.04	.90	-3.21	47.8	.002
	Label	-.52	1.46			

Note: M = mean, SD = standard deviation, t = t test statistic, df = degrees of freedom, p = significance.

Difference in brain activity difference for human labels and computer labels

Our main interest was whether there were differences between anticipation or expectation of human-made art and computer generated art, which we investigated by testing if the two primes elicited different brain activity in the participants. For each ROI, we calculated a paired-samples t-test to examine whether there was a significant difference between activation when being presented with the human label vs. with the computer generated label. Outliers and participants who claimed to have ignored or not believed the labels in the post-questionnaire were excluded for this analysis, resulting in a sample size of 35 for this analysis. The descriptive statistics and the test results for each label in each brain region are shown in Table 5 and boxplots visualizing the results are depicted in Figure 11a-d. No test showed a significant activity difference between the two labels.

Table 5

Descriptive data and results of t tests between human and computer label for each monitored brain area

ROI	Label	N	M	SD	t	df	p

mPFC	Human	509	-.558	1.55	.507	543	.61
	Computer	524	-.607	1.53			
lTPJ	Human	474	-.603	1.49	.599	527	.55
	Computer	474	-.658	1.36			
rIFG	Human	490	-.407	1.63	-1.244	543	.21
	Computer	496	-.531	1.5			
O1	Human	490	-.547	1.46	-.559	543	.58
	Computer	486	-.494	1.46			

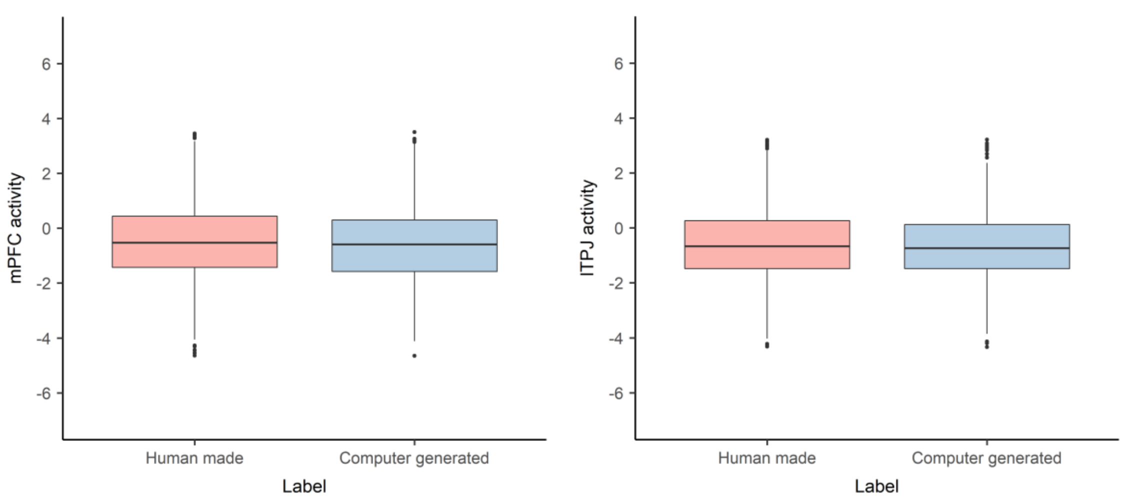
Note. N = sample size, M = mean, SD = standard deviation, t = t test statistic, df = degrees of freedom, p = significance.

Even though the tests were not significant, note that there was a slight trend that the activity was lower for "computer generated"- labels than for "human artist"- labels.

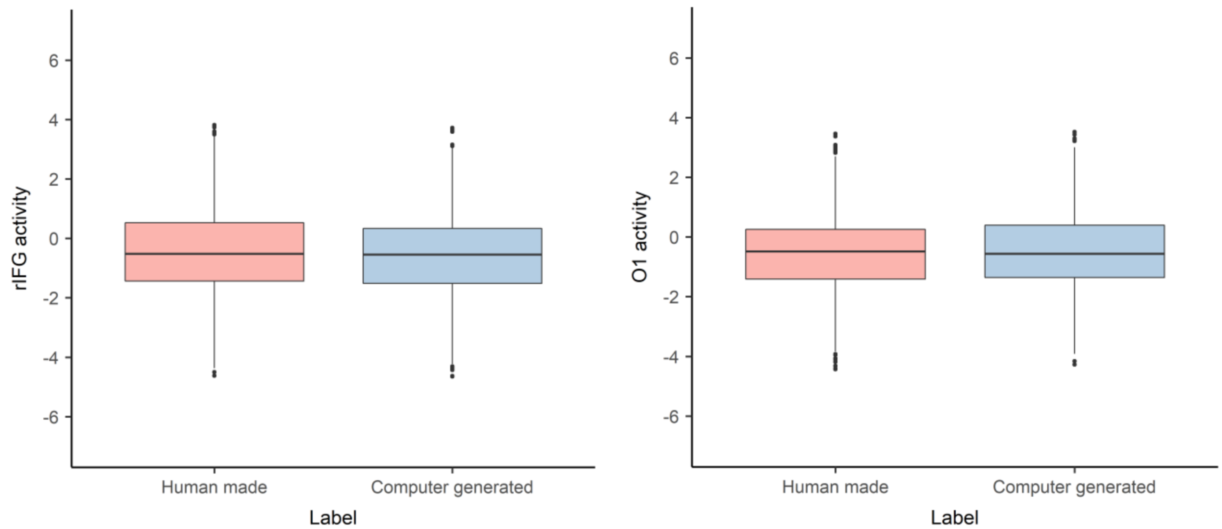
Figure 11a-d

Boxplots depicting differences in brain activity when being presented with the human label "human" and the label "computer generated".

a) mPFC *b) lTPJ*



c) *rIFG* *d) O1*



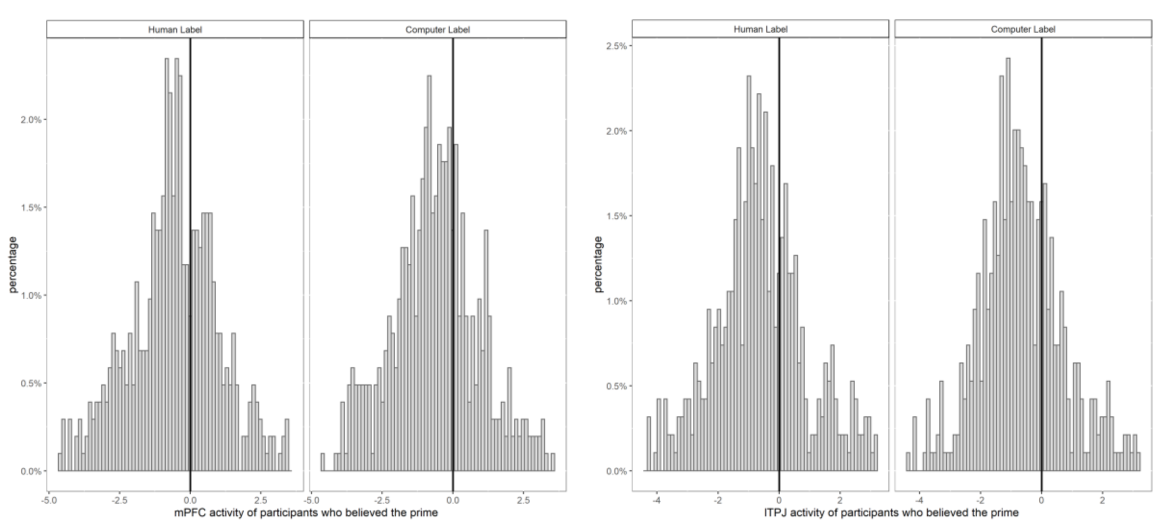
Note: Brain activity is z-scored for all ROIs: Coxy-Hb z Score (oxygenated hemoglobin)

Figure 12 a-d shows histograms of participants' mean brain activity during the label viewing for each area monitored, excluding participants who claimed to have ignored or not believed the labels at all.

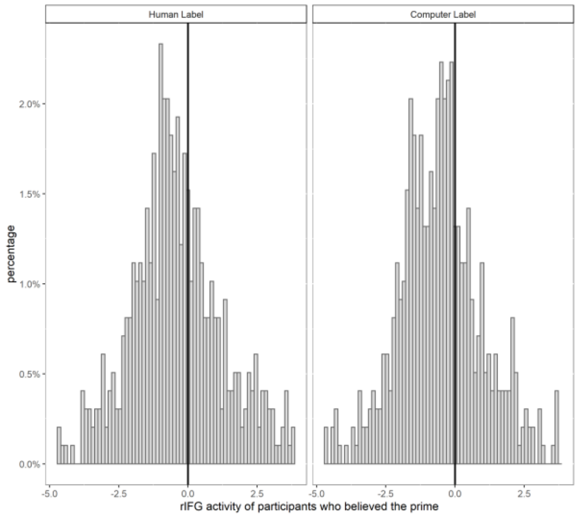
Figure 12 a-d

Mean brain activity during expectation period

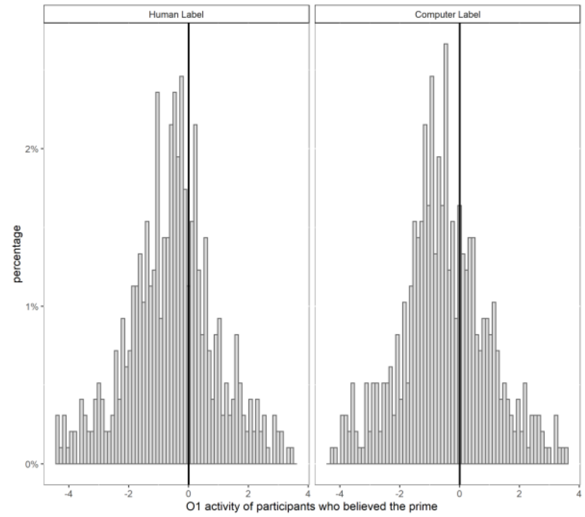
a) mPFC *b) lTPJ*



c) rIFG



d) O1



Note: Brain activity is z-scored for all ROIs: Coxy-Hb z Score

Brain activity during the whole trial (viewing prime and picture)

To create an overview of the brain activity during the whole trial, we visualized the mean brain activity for different prime-picture combinations in each ROI during the whole trial. These graphs are presented in Figure 13a-d to Figure 17a-d. The vertical line at the 10 second mark represents the switch between seeing the label and seeing the picture on the screen. For Figure 13, each graph shows all four prime and picture type combinations per ROI. For Figures 14-17, the separate lines differentiate both the computer and human picture category by representative art (landscape art) and abstract art (pixel pictures).

Moreover, we examined whether the mean brain activity was different during viewing the label than during viewing the picture in general, regardless of the type of label and picture category. We conducted t-Tests of the prime data and the picture data for each ROI (Table 6). There was a significant difference of brain activity when viewing the label and when viewing the picture for all regions monitored. Mean activity was higher when viewing the picture than when viewing the label. This indicates that brain activity is more pronounced during viewing the art than during the expectation period.

Table 6

Results of t tests between viewing the label and viewing the art for each monitored brain area

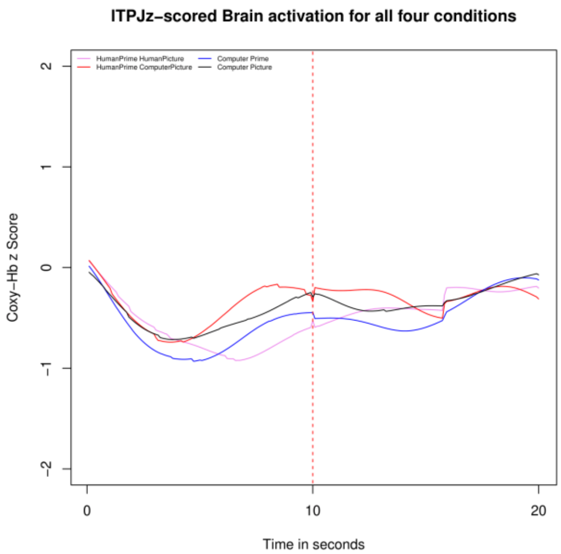
ROI	Trial	M	SD	t	df	p
mPFC	Prime	-.582	1.54	-4.53	2066	<.001
	Picture	-.278	1.52			
lTPJ	Prime	-.630	1.42	-4.42	1893	<.001
	Picture	-.328	1.57			
rIFG	Prime	-.470	1.57	-2.99	1996	.003
	Picture	-.260	1.57			
O1	Prime	-.521	1.46	-6.50	1944	<.001
	Picture	-.070	1.60			

Note: M = Mean, SD = standard deviation, t = t test statistic, df = degrees of freedom, p = significance.

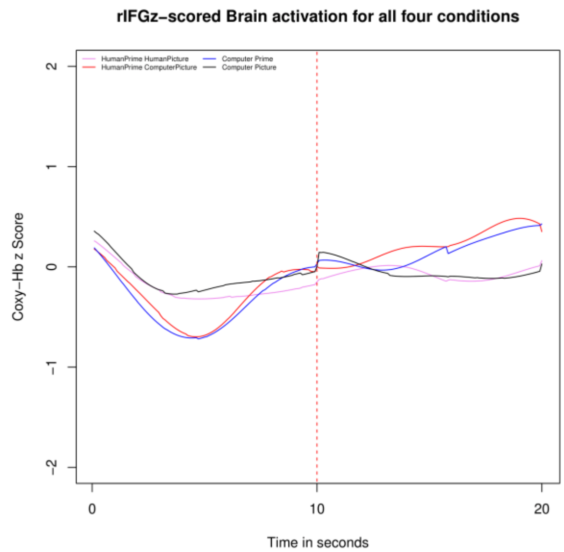
Figure 13 a-d

Average z-scored brain activity during trials containing all prime and picture combinations

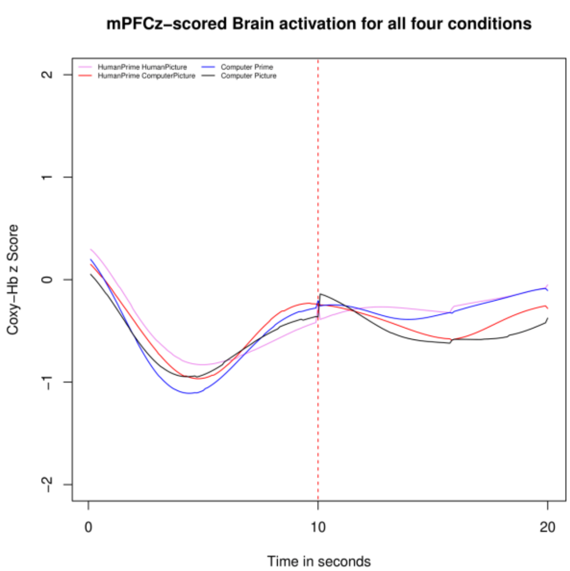
a) lTPJ



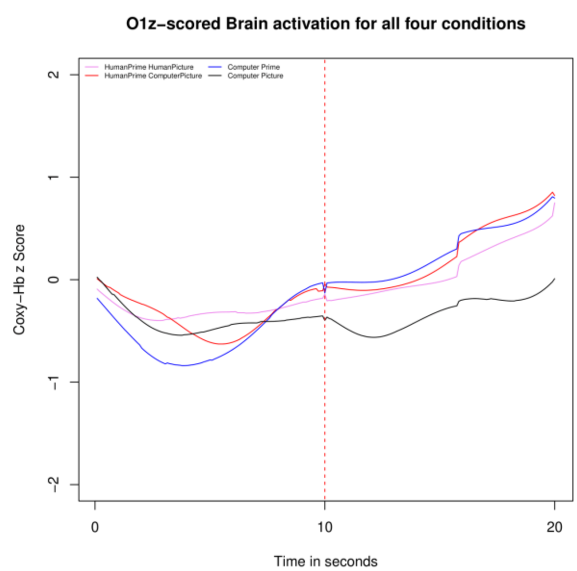
b) rIFG



c) mPFC



d) O1

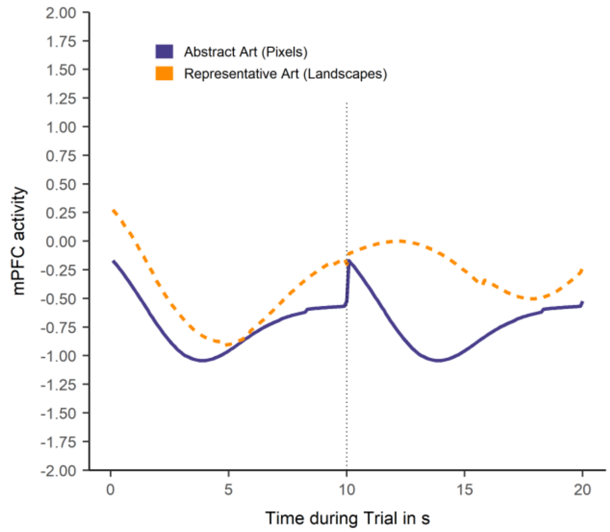


Note: Brain activity is z-scored for all ROIs: Coxy-Hb z Score

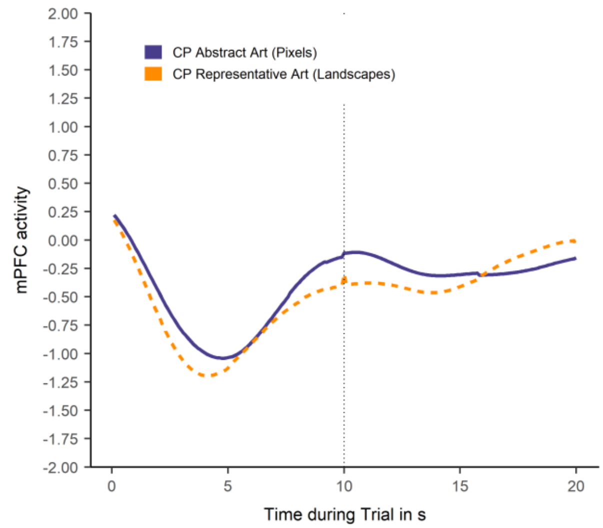
Figure 14 a-d

Average z-scored brain activity in mPFC during trials, separated by prime/picture combination

a) Computer Labels, Computer Pictures

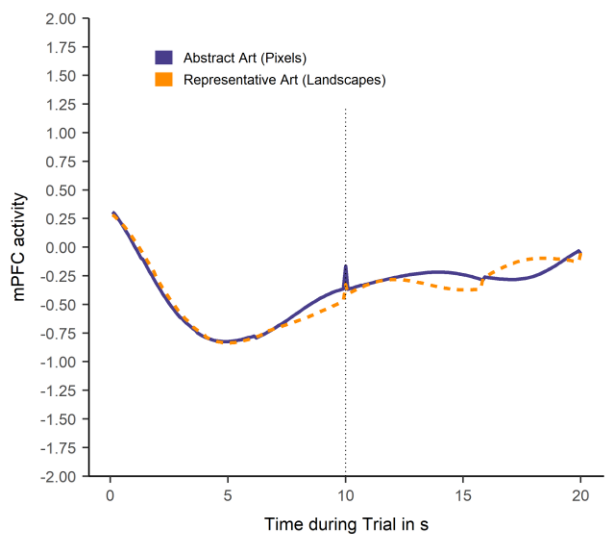


b) Computer Labels, Human Pictures

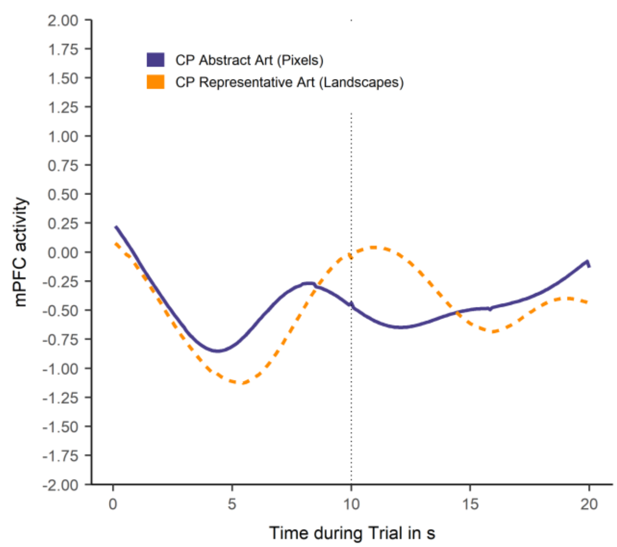


c)

Human Lables, Human Pictures



d) Human Lables, Computer Pictures

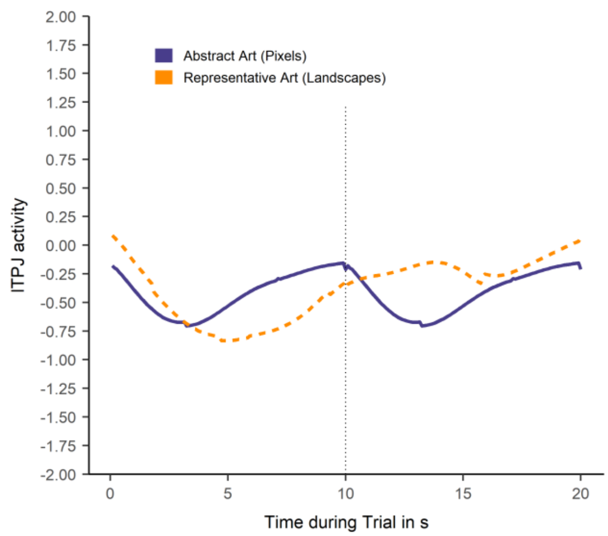


Note: mPFC Coxy-Hb z Score

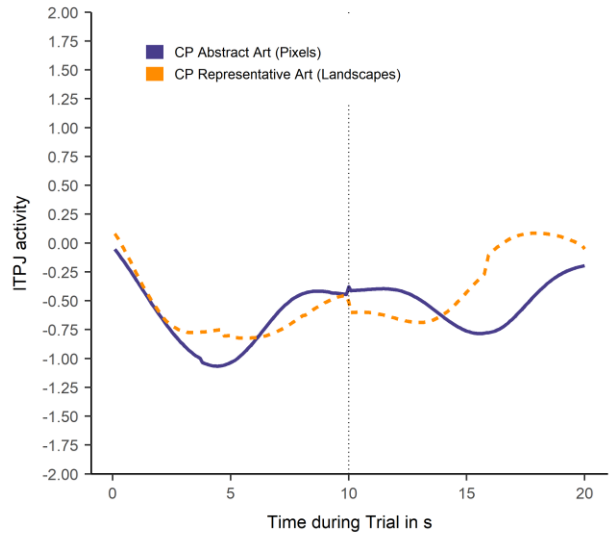
Figure 15 a-d

Average z-scored brain activity in lTPJ during trials, separated by prime/picture combination

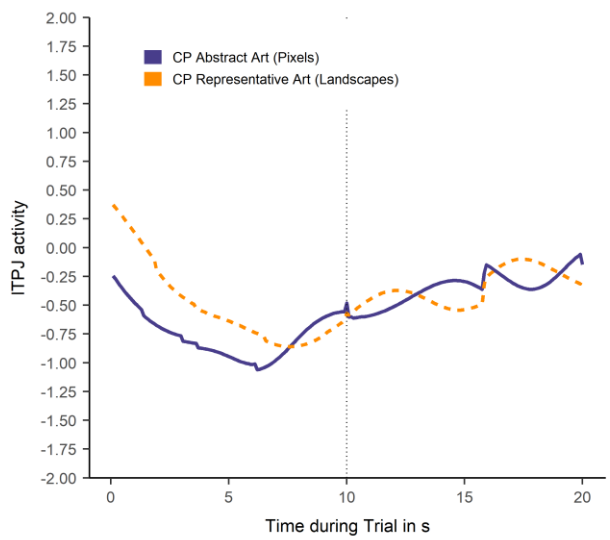
a) Computer Labels, Computer Pictures



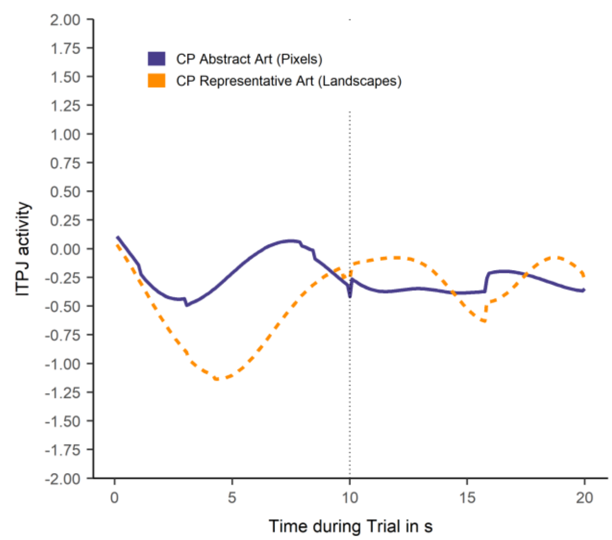
b) Computer Labels, Human Pictures



c) Human Lables, Human Pictures



d) Human Lables, Computer Pictures

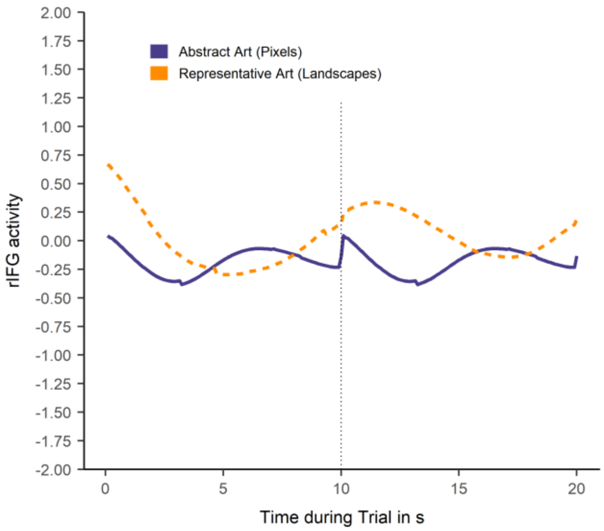


Note: lTPJ Coxy-Hb z Score

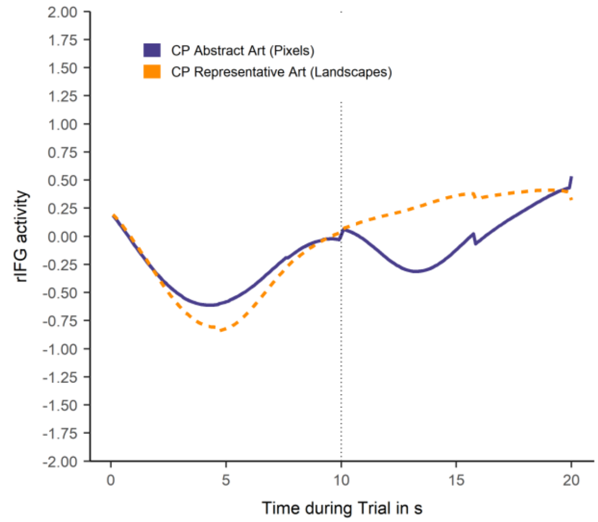
Figure 16 a-d

Average z-scored brain activity in rIFG during trials, separated by prime/picture combination

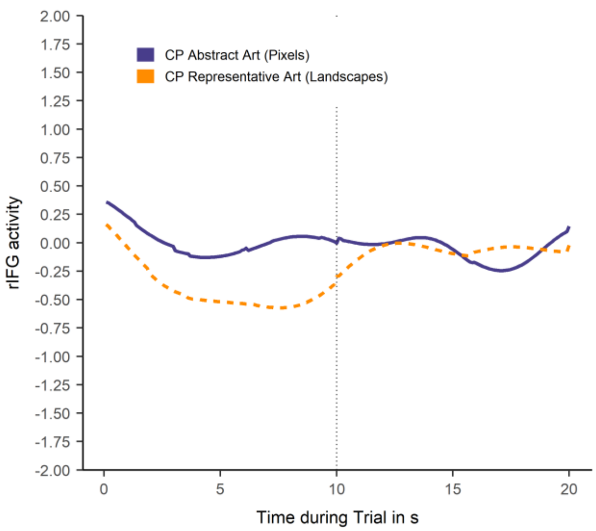
a) Computer Labels, Computer Pictures



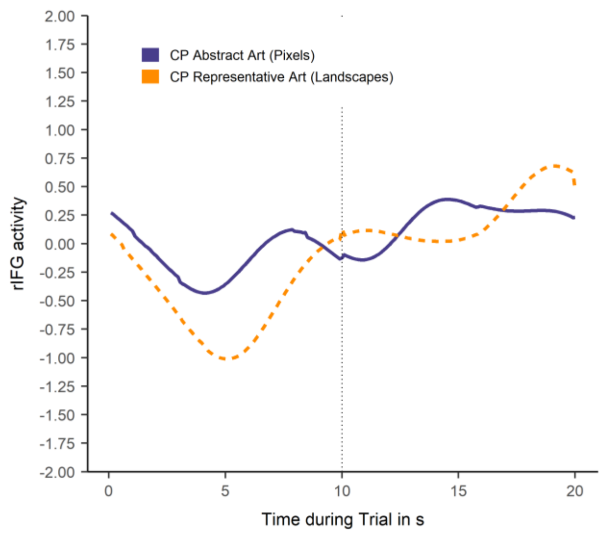
b) Computer Labels, Human Pictures



c) Human Labels, Human Pictures



d) Human Labels, Computer Pictures

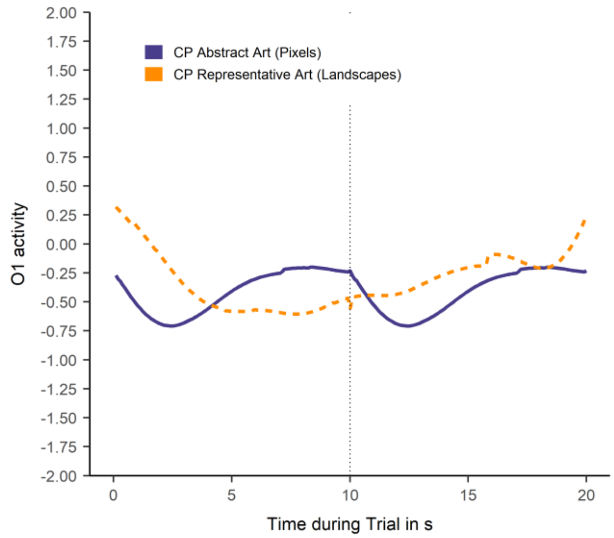


Note: rIFG Coxy-Hb z Score

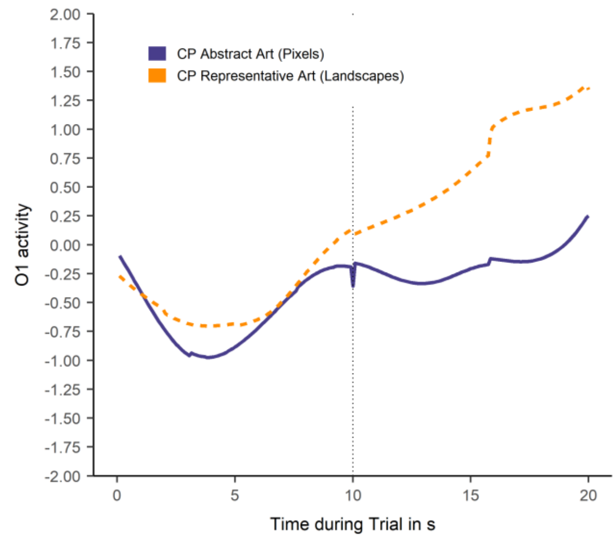
Figure 17 a-d

Average z-scored brain activity in O1 during trials, separated by prime/picture combination

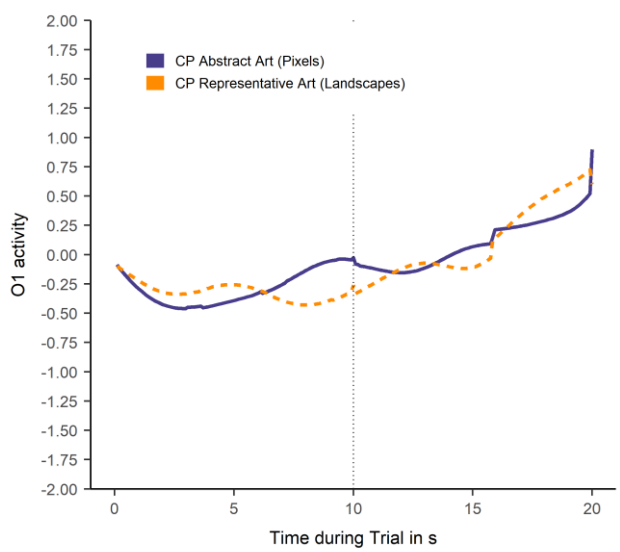
a) Computer Labels, Computer Pictures



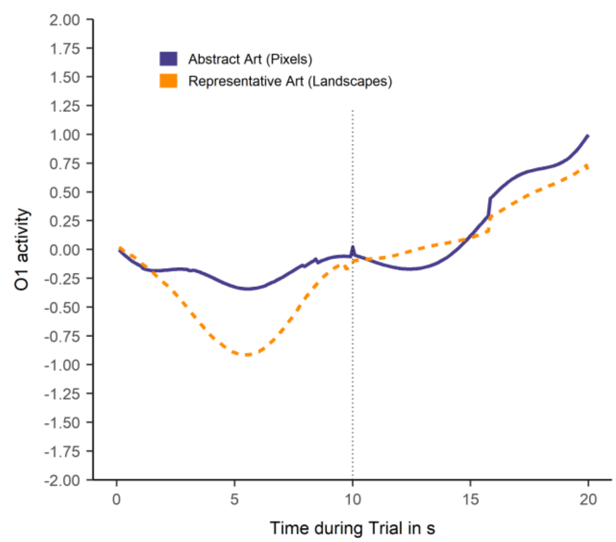
b) Computer Labels, Human Pictures



c) Human Lables, Human Pictures



d) Human Lables, Computer Pictures



Note: O1 Coxy-Hb z Score

Difference in brain activity for each each prime-picture combination

Next, we aimed to examine the activation pattern for each prime-picture combination during the viewing period of the art, and how the label, the picture category or an interaction of both influenced the viewers' brain activity. For this, we conducted a two-way repeated measures ANOVA investigating main effects of prime, of picture category and of their interaction for each brain area monitored. For each Prime*Picture interaction, the Huynh-Feldt adjustment was used to correct for violations of sphericity. None of the tests yielded statistically significant results, which can be seen in Table 7. Figures 18 a-d show the data from these analyses, displaying that the activity differences were too small to yield significant results. Each graph shows the mean activity of each region, with the errorbars representing the standard deviation.

Table 7

Descriptive data and results of ANOVA

ROI	Prime					Picture					Prime x Picture				
	F	df1	df2	p	*pη2*	F	df1	df2	p	*pη2*	F	df1	df2	p	*pη2*
mPFC	.39	1	39	.54	.004	.02	1	39	.90	.001	.01	1	39	.91	.001
lTPJ	.08	1	38	.77	.001	.58	1	38	.45	.006	.25	1	38	.62	.001
rIFG	.07	1	39	.79	.001	.60	1	39	.44	.006	.04	1	39	.85	.001
O1	.39	1	39	.54	.004	.10	1	39	.75	.001	.13	1	39	.72	.001

Note. N = sample size, M = mean, SD = standard deviation, t = t test statistic, df = degrees of freedom, p = significance.

Figure 18a

Interaction: Mean mPFC activity per Picture Category, grouped by Prime

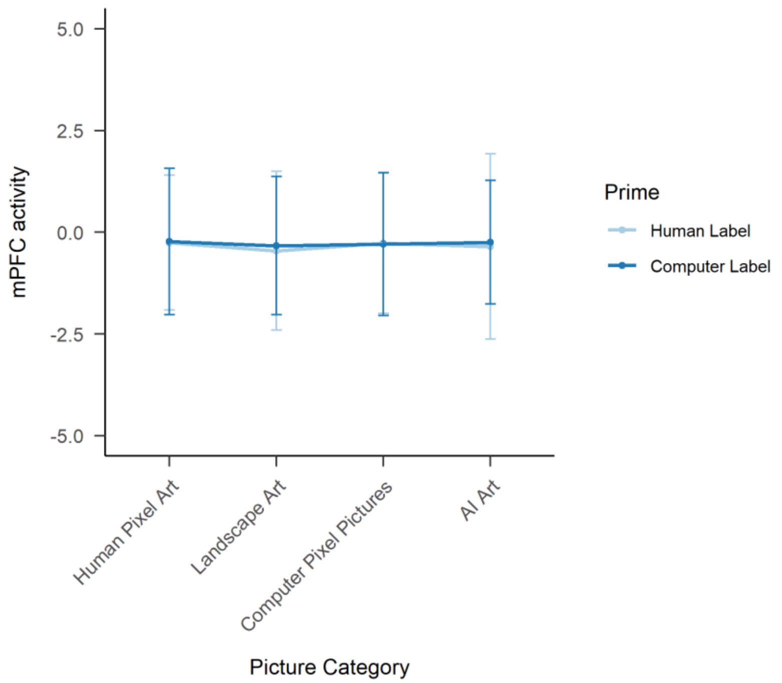


Figure 18b

Interaction: Mean lTPJ activity per Picture Category, grouped by Prime

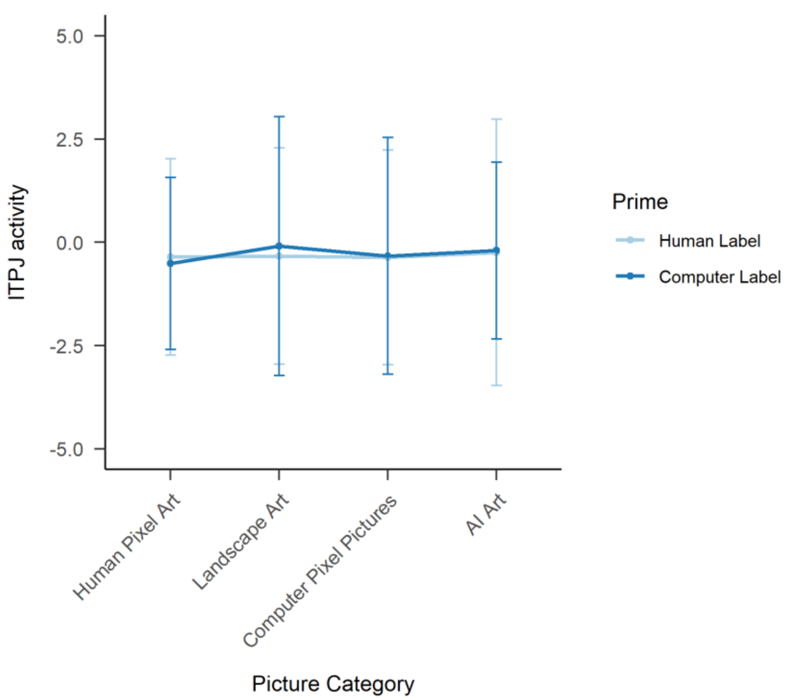


Figure 18c

Interaction: Mean z-scored rIFG activity per Picture Category, grouped by Prime

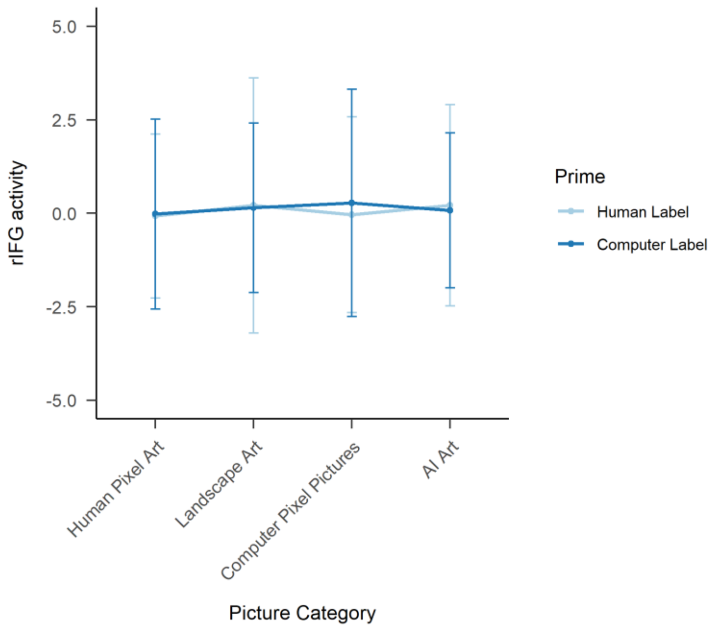
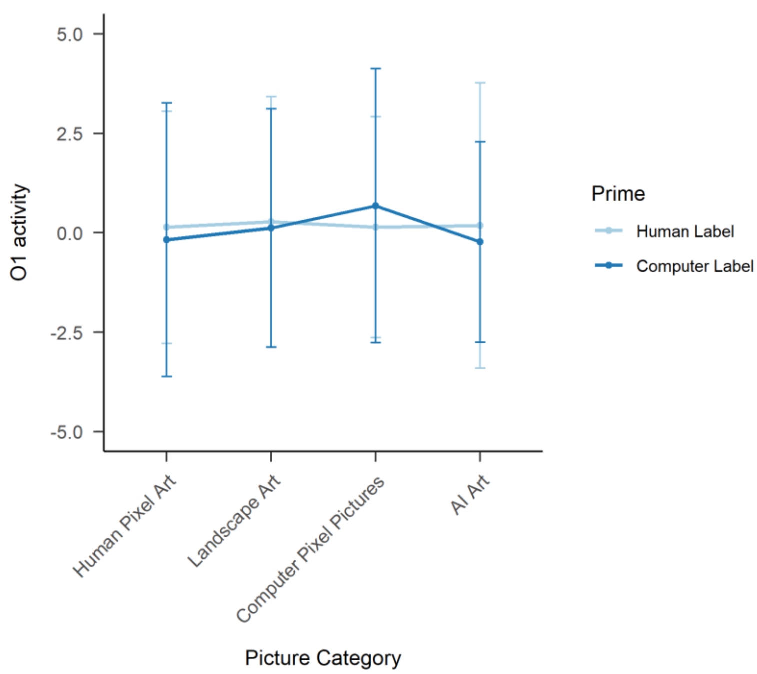


Figure 18d

Interaction: Mean z-scored O1 activity per Picture Category, grouped by Prime



Was brain activity related to people's empathy scores?

To answer this question, we calculated correlations between the brain data and participants' scores for affective empathy and cognitive empathy, which were taken from the QCAE results of the pre-questionnaire. There was no significant correlation between any of the variables. Moreover, there was no significant correlation between the brain activation and any of the other variables collected in the pre-questionnaire, namely previous knowledge about AI art, previous art experience, opinions about authorship in AI art, openness to emotion transmission in art or opinions about art forgeries or art made by children and animals. Correlation matrices are in Table 13-16 in the appendix.

Do people with higher empathy scores rate human pictures higher in behavioural ratings than people with lower empathy scores?

To answer this, we calculated correlations between each QCAE empathy trait and each stimuli category for each rating variable. However, none of the analyses yielded significant results. Moreover, we were interested whether there was a correlation between the data collected in the pre-questionnaire and the ratings. (Table 8)

For the liking ratings, there was a positive correlation between previous art experience and the liking of human representative art with a truthful human prime ($r = 0.37$, $p = 0.042$). There was also a positive correlation between openness to emotion transmission in art and liking of human representative art with a false computer prime ($r = 0.31$, $p = 0.044$). For intention, there was a positive correlation between openness to emotion transmission in art and perceived intention in human representative art with both the truthful human prime ($r = 0.33$, $p = 0.03$) and the false computer prime ($r = 0.35$, $p = 0.019$). Moreover, there was a positive correlation between previous art experience and perceived intention in human representative art with both the truthful human prime ($r = 0.34$, $p = 0.043$) and the false computer prime ($r = 0.36$, $p = 0.031$). Concerning felt emotion, there was a positive correlation between the openness to emotion transmission in art and human representative art with both the truthful human prime ($r = 0.33$, $p = 0.035$) and false computer prime ($r = 0.30$, $p = 0.024$) and human pixel art with both the truthful human prime ($r = 0.35$, $p = 0.022$) and the false computer prime ($r = 0.31$, $p = 0.046$). For felt connection, there was a positive correlation between previous knowledge about AI art and human pixel art with a truthful human prime ($r = 0.38$, $p = 0.048$). There was also a positive correlation between openness to emotion transmission in art and human representative art with a truthful prime (r = 0.43, p = 0.004) and human pixel art with a false computer prime (r = 0.33, p = 0.026).

Table 8

Correlations between pre-defined traits/opinions and picture ratings

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. Previous Art Experience	-													
2. Emotion Transmission	.41	-												
3. Previous Knowledge about AI Art	.33	-.11	-											
4. Liking, HPrHumRep	**.37**	.19	.09	-										
5. Liking, CPrHumRep	.23	**.31**	.25	.71	-									
6. Intention, HPrHumRep	**.34**	**.33**	.06	.53	.39	-								
7. Intention, CPrHumRep	**.36**	**.35**	.35	.64	.70	.78	-							
8. Emotion, HPrHumRep	.16	**.33**	-.07	.55	.42	.61	.72	-						
9. Emotion, CPrHumRep	.19	**.30**	-.02	.50	.56	.75	.86	.83	-					
10. Emotion, HPrHumPix	.26	**.35**	.16	.23	.33	.42	.58	.54	.67	-				
11. Emotion, CPrHumPix	.16	**.31**	.20	.12	.34	.39	.52	.48	.62	.87	-			
12. Connection,	.31	**.43**	-.08	.57	.32	.86	.71	.82	.73	.82	.32	-		

HPrHumRep														
13. Connection, HPrHumPix	.05	.16	**.38**	.16	.19	.39	.38	.39	.54	.65	.66	.32	-	
14. Connection, CPrHumPix	.22	**.33**	.28	.18	.28	.47	.50	.41	.56	.72	.81	.39	.87	-

Note. M and SD represent mean and standard deviation. HPrHumRep = representational landscape art with a human label, CPrHumRep = representational landscape art with a computer label, HPrHumPix = pixel picture made by human artist with human label, CPrHumPix = pixel picture made by human artist with computer label

Was brain activity for each picture category related to humanness rating instead of the prime?

Since the primes did not seem to significantly influence brain activity during anticipating and viewing the artworks, we wanted to know whether brain activation was different for each picture category based on peoples' humanness ratings. To assess this, we investigated whether brain activity and humanness ratings were correlated by calculating Kendall-Tau correlation. For this, we only considered the viewing period as humanness ratings were expected to connect to viewers' visual assessment of the actual art. There was no statistically significant correlation between the humanness ratings and the activity of any brain area monitored. The results are listed in Table 9.

Table 9

Correlation of each ROI with participants' humanness rating

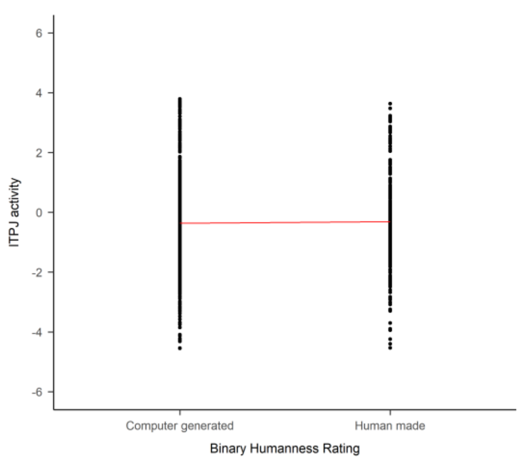
ROI	mPFC	lTPJ	rIFG	O1
z	1.048	-.159	1.218	-1.486
Tau	.022	-.004	.026	-.032
p	.147	.563	.112	.931

For Figure 19 a-d, we converted the humanness rating scale to a binary format, thus valuing every rating under 3.5 as “seems more human” and every rating above 3.5 as “seems more computer generated”, to get an overview of trends in the data. For all regions connected to empathy and ToM, brain activity was higher when viewing pictures that participants then rated as human made, than when viewing pictures they rated as computer generated. Only for the control visual area O1, the trend is inverted so that there was slightly less activity for pictures that participants rated more human. However, in paired t-Tests investigating these trends, all differences are too small for producing a significant effect.

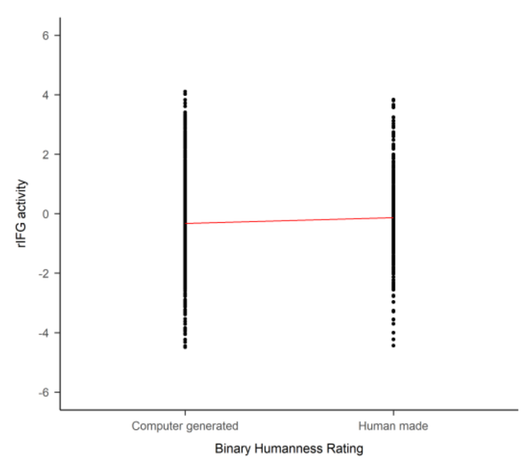
Figure 19 a-d

Brain activity while viewing the picture, grouped by participants’ humanness ratings

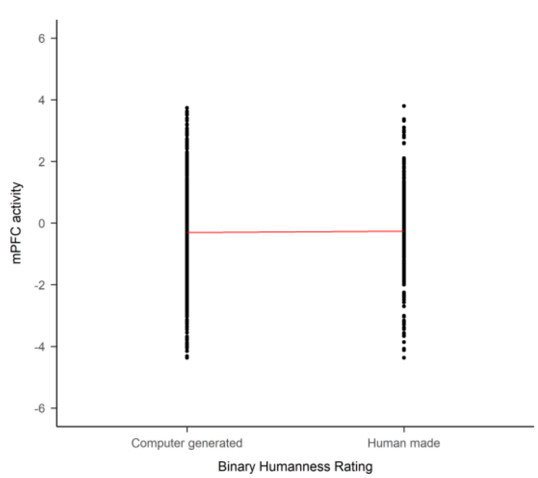
a) lTPJ



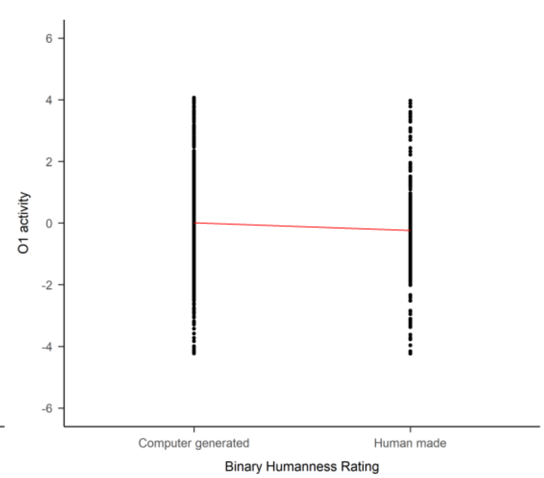
b) rIFG



b) mPFC



d) O1



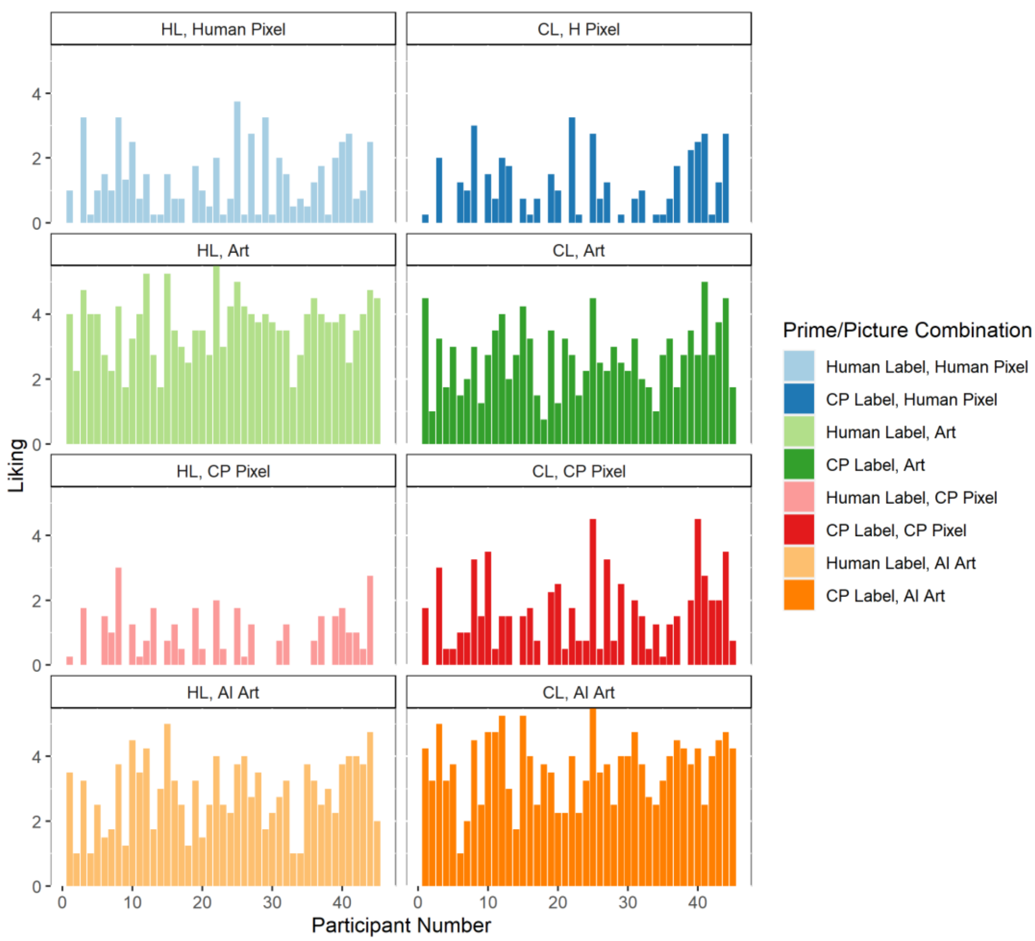
Note: Brain activity is z-scored for all ROIs: Coxy-Hb z Score

Interpersonal differences in the ratings

To recognize possible interpersonal differences or notable patterns in individuals, we illustrated the mean ratings for each variable (liking, connection, intention, emotion) in each stimuli category per participant. Figure 20 shows the graph for the variable liking. The figure shows that for each variable, there were interpersonal differences in the ratings regardless of prime/picture combination, with some participants giving higher ratings than others in general. Since the interpersonal differences were similar for all variables, just one graph is included. All other graphs can be found in the appendix (Figure 21-23).

Figure 20

Mean Liking Rating of each Participant per Picture Category



5. Discussion

In this study, we explored new areas of research on emotional response to art by investigating the anticipation and expectation of human made versus computer generated art. Moreover, we analysed to what extent the label provided shaped the behavioural and brain-based empathic and emotional response before and during viewing different types of art. To achieve this, we provided a collection of highly similar digitally produced abstract art made by human artists and made with a random computer generator and a collection of similar landscape art made by renowned human artists and made with either a GAN or a CAN network.

In the following section, we will discuss the results in more detail and link them to previous research. First, we focus solely on the expectation period, where viewers were provided with the label before viewing each picture, to explore the main research interest: *Do people anticipate the viewing of art empathically? If so, does this anticipation differ for art labelled to be made by a human artist vs. computer generated?* To answer this question, we investigated whether there was brain activity during viewing the label and anticipating the art that would suggest the anticipation or expectation of a 'social' interaction with the art. Going one step further, we were interested in the difference between expectation of art by a human artist and computer generated art. We found evidence that brain activity is lower in empathy regions of the brain (mPFC, lTPJ, rIFG) when anticipating art than when being told to relax. Thus, we did not find evidence that people prepare to view art by not only anticipating an empathic interaction through the artwork. Moreover, there was no clear difference between brain activity when expecting human made art and expecting computer generated art.

Our second research interest was: *To what extent does the label provided shape the behavioural and brain-based empathic and emotional response when actually viewing different types of art?* To investigate this question, we considered the interactions between the label and the type of art. We found that the label provided again did not have a strong influence on people's behavioural ratings of the pictures nor their brain activity during viewing the art. The type of art and the actual source, regardless of the label, were better indicators of responses to the art. This was especially evident in the behavioural responses that collected peoples' self-rated emotional responses to the artwork.

5.1 fNIRS Data

Is there brain-based evidence that people anticipate art in empathy regions of the brain?

As previously stated, we did not find evidence for a clear empathic anticipation in the period before viewing art in the brain areas. Brain activity was lower when seeing the label than when being asked to relax in all three empathy and ToM regions and in the visual area monitored as comparison. We tested this with t-tests comparing the mean brain activity under these two premises. The lower activation during the anticipation does not provide evidence that people anticipate or prepare for an empathic or "social" interaction with an artwork, as is proposed in Pelowski et al.(2017) and Kühnapfel (2020). The second part of our research question was whether the anticipation differs for human labels and computer generated labels. The activation was not significantly different for the two opposing labels (human made/computer generated). This could mean that the source of the artwork is not essential for the preparation for an empathic connection to the artwork and suggests that the humanness of the artist is not a crucial aspect in the communication happening through the artwork. Another possible reason is that viewers did not perceive the label "The following artwork was computer generated" as stripped entirely of humanness. Participants might automatically ascribe some remnant of humanness or autonomy to the process of generating art on a computer, even if that just consists of clicking the buttons to generate a mostly random abstract picture or separating the program from the programmer and still ascribing some independence to it, as was found by Sundar&Nass (2000). This highlights the difficulty and dilemma around ownership, authorship and copyright in computer generated art and supports the extent of the tendency to ascribe agency described in previous research (Müller et al., 2018; Nass & Moon, 2000). There was a trend in our data that brain activity in empathy-related regions (mPFC, lTPJ, rIFG) was higher when viewing the human label than when viewing the computer label. However, this difference was not pronounced enough to yield a significant effect in the data. Thus, it cannot be statistically expressed that human labels yielded higher activity in the monitored regions than computer labels.

To summarize, the results for this question show that there is activity in empathy-related regions of the brain when anticipating art, but there is no evidence that this activation is different for anticipating human made art than for expecting computer generated art. Thus, the label does not seem to be the most crucial aspect for shaping expectations and short-time anticipation of art.

How does brain activity change when the picture appears?

Our second research question concerns the empathy activity during viewing different types of artworks and whether there is an interaction of the prime and the picture type that influences brain activity in the monitored regions. Firstly, testing revealed an overall brain activity difference between the expectation and the actual viewing period, suggesting that the activity in the monitored regions changed with the onset of the picture. This supports the notion that art-viewing is partly an emotional or empathic experience, including connection and a form of communication through the artwork, as was advocated by Pelowski et al. (2017) and Kühnapfel et al. (2020).

However, brain activity again did not differ significantly between the different types of art. Moreover, it neither changed significantly dependent on the actual source (artist/computer) or the alleged source (prime). Thus, our results suggest a different pattern in empathy areas than might be expected when considering results by Kirk (2009) or Huang et al. (2011) implying that the label alone is enough to significantly alter people's brain activity in reward areas during viewing the same art with different labels. Moreover, brain activity did not increase with the complexity of the art or with the amount of human traces in the artwork, as might be expected considering that art with more traces of a human artist has been found to increase activity in motor areas (Umilta et al., 2012, Sbriscia-Fioretti et al., 2013).

Our findings might be an indication that people are able to overcome a possible bias against computer generated art (Hong & Curran, 2019). This would suggest viewers in this study either held no presumptions or negative stereotypes regarding computer generated art or the degree of humanness of the actual or believed source does not influence the emotional or empathic interaction with art as strongly as research in other brain areas would suggest (Kirk et al., 2009, Huang et al., 2011). Further research is needed to collect more nuanced evidence for a reliable interpretation of this finding.

If the activity was neither significantly dependent of the prime nor on the picture type, was it related to empathy score of individuals or to people's own perception/rating of how human the source seemed to be?

Another interest of this project was to couple brain activity in the regions monitored to empathy scores people self-reported on the QCAE, which was given to each participant before entering the study. We found no correlation between self-reported empathy scores and brain activity in regions concerned with empathy and perspective-taking. Findings by Gerger et al. (2018) suggested a differentiation in emotion contagion according to people's empathy scores. Thus, we theorized this difference would be translated or visible in brain activity as well. However, our results cannot provide evidence for the notion that individuals with higher affective and cognitive empathy would show more pronounced differences in brain activity in reaction to the "human made" labels or the actual artworks made by humans.

Since the brain activity monitored was neither dependent on the prime nor on the picture type nor was it correlated with the trait empathy, we explored a connection between brain activity and participants' ratings of how human the source of each picture seemed to them. While the test showed no significant correlation, brain activity was higher in the three empathy-related areas when participants believed the picture to be more human made than computer generated. This nonsignificant trend suggests a small tendency of higher empathy activity when people believed the source to be human, regardless of the actual origin or the label provided. This would support that the perceived source is more important for appraising and experiencing art than the actual source, as Foucault, (2019) suggested. Only for the visual comparison area this trend was reverse, so the activity was nonsignificantly higher when people believed the picture to be computer generated. Even though in Huang et al. (2011), there was no significant difference in lateral visual cortical areas, they found that when labelled as a copy, viewers reported trying harder to detect flaws in an artwork than when labelled as an original. This could point to the interpretation that participants looked at the painting more closely when they thought it to be computer generated, which would explain the nonsignificant higher engagement of the visual area. This might indicate that people assume a human artist as default source of any picture framed as art, and when their default mode is challenged by questioning of the source's humanness, the visual integration of source and content might take more effort or viewers might be more inclined to look for traces or hints of the computer generation.

Overall, the brain data showed different activation for each of the steps in expectation of and during art appraisal. However, the difference between anticipation of human art and anticipation of computer generated art were not distinct enough to produce significant effects.

5.2 Behavioural Data

While the project's main interest lay in the fNIRS research and data, we also collected behavioural data to complement our findings and to link our study to previous and similar research done in this field. These findings are the result of questions participants were asked after viewing the picture. Thus, they mostly refer to the viewing experience rather than our main interest, the expectation of the viewing experience. Regardless, these insights are crucial to understand people's emotional experience and understanding of each picture.

How human and computer generated was each category rated?

This question enables an overview on how often people believed the prime and how often the prime would fade into the background in favour of the actual source of the picture. Both the human made and the AI generated representative, colourful landscape pictures were more often rated as coming from a human artist than both the human made and computer generated abstract digital art. This indicates a bias against the digitally produced pixel art, which was also evident in the open responses in our post-questionnaire (e.g. "The pixel pictures were annoying and bad, regardless whether they were made by a human or computer generated.", all answers are listed in Table 11 in the appendix) and is backed by viewers usual preference for more complex stimuli (e.g. Jacobsen et al., 2005). Comparing these two categories of art, it seems that participants equated more complex and layered art with a human source and ascribed the digital black-and-white pictures more often to a computer source. For most ratings, the two complex landscape art categories also received higher ratings of liking, perceived intention, felt emotion and perceived connection than both digital pixel art categories, which highlights this presumed bias.

Another point we want to emphasize is the humanity ratings of the completely randomly computer generated pictures. We explored whether this specific category of pictures would even in some cases be ascribed a certain human, emotional component and whether people could feel a connection with even this completely random array of black and white squares. While this category was the one that elicited the least emotion, connection and perceived intention, we still found that people could feel a connection, emotion and even intention in completely randomly computer generated art to some degree. While these ratings were higher when the pictures were combined with the human label, they even elicited some degree of emotion, connection and intention when combined with the computer label. This dynamic was only different for the mean liking rating, where the pictures were liked more when paired with the computer label. The fact that even these completely random pictures were not completely perceived without any emotional or connecting elements can once more be linked to the tendency to ascribe agency to an object or machine. This compliments a similar finding by Demmer (2021), and the general tendency to ascribe agency has been suggested by Müller et al., 2018 and Nass & Moon, 2000). Again, this shows that the perceived source with some degree of ascribed agency is more important for appraising and experiencing art than the actual source (Foucault, 2019), as the perceived humanness of the artist seemed to matter more than if there was an actual human origin.

Interestingly, the highly similar abstract art made by human artists elicited higher ratings than the computer generated abstract pictures in most questions. Most closely, we analysed this difference for the ratings of humanness of the artist. The pictures with an actual human source elicited higher humanness ratings than the computer generated ones, indicating that people can sense a human sender through the artwork. Matching results found by Snapper et al. (2015), there might be an innate trace of the human artist even in the abstract pixel art. Our findings moreover suggest that this human quality or marker does not have to consist of brushstrokes or other visible traces of the artist, which is in accordance to results by Demmer (2021). Even the highly similar pixel art has some human quality to it that participants can notice or sense, regardless of the label provided with the art.

Does the prime or the picture influence people's ratings more?

Our next question concerned the influence that either the prime, or the picture type, or an interaction between the two influenced the behavioural ratings the most. The testing confirmed that the prime did not influence ratings significantly, but that rather the picture type is critical for the ratings. As described above with the humanness ratings, viewers perceived more intention, connection and felt more emotion when being presented with the two more complex, colourful picture categories than with the pixel pictures, regardless of the actual source and regardless of the label used. For the perceived humanness of the source, the emotion felt during viewing, the connection perceived to the picture, and the intention perceived in the picture, the ratings were higher for the landscape art that was actually made by human artists than the AI generated landscape art. This is supporting evidence that viewers feel more intense emotion and connection towards art made by humans. This was true for both labels, which again aligns with findings by

Hawley-Dolan & Winner (2011) or Snapper et al. (2015), that there is some innate quality to human-made art that can be sensed regardless of the label provided.

While the prime did not have a significant effect on people's ratings, in most categories there was a trend that pictures with a human label still elicited more emotion, liking, connection and perceived intention than pictures combined with a computer label. Only the liking of both the computer generated pixel pictures and the landscape art generated with AI was higher when these pictures were paired with a computer label. According to the data, people could discern the categories by a computer source (even unknowingly) and provided them with more praise when told that these pictures were generated than if they were made to believe that it is coming from a human artist. As mentioned above, only for liking, computer generated pixel pictures and the landscape art made with an AI were rated higher when paired with the computer label. This can be viewed in line with findings by Szubielska (2020) which show that ambiguous artworks paired with contextual information about an artist's impairment or disability are liked more than the same art without the information provided. In our case, the label "computer generated" can be seen as contextual impairment, in the sense that viewers were for example more impressed with or thought to understand and therefore like the computer generated art more if they believed it to be generated by a program. Likewise, viewers did not share the same feelings if the contextual information pointed to the default mode, which is a human artist.

Do people with higher empathy scores rate human pictures higher than people with lower empathy scores?

Similar as with the NIRS data, we were interested about a connection between the behavioural ratings and empathy scores. There was no evident correlation between the ratings and empathy scores of viewers in our data.

However, there were correlations to factors concerning familiarity with art and AI that we collected from all participants: People who claimed to have more previous experience with art showed higher liking for representative art made by humans, only showing in trials that contained a human label. They also felt more connection with the human made pixel art if it had the human label This may highlight that the human label confirmed the innate quality of human art as described by Hawley-Dolan & Winner (2011) and Snapper et al. (2015), which might lead to more rating confidence in people who have experience with art and might be familiar with the feeling of viewing art made by human artists. Moreover, people with more prior art experience could also feel more intention in the human landscape pictures, for this variable with both labels provided, which suggests that this instinct about the humanness of the artist and their intention of the artwork is stronger than the prime in this art category.

A correlation indicated that people who were more open to the concept of emotion transmission in both human made and computer generated art liked the human made representative art in trials labelled as computer generated more than people who were less open to emotion transmission. While this openness might lead to more appreciation of the technical advances needed to create art that elicits emotion and that people can connect to, there was no correlation that participants who were less open to emotion transmission in art felt similar about this facet of representative art labelled as computer generated. The same openness also correlated with perceived intention and felt emotion in this art category, for this variable this correlation affected both trials with human labels and trials with computer labels. This might indicate that people who were more open to emotion transmission in both human made and computer generated art were less concerned with the label and what it might indicate, but were able to feel more intention behind this art category because they did not feel like computer art would not be able to elicit the same reactions as human made art. To support that, the same people also felt more emotion with the pixel art made by human artists, regardless of the label. Concerning the connection people with more openness felt during viewing, more openness to emotion transmission also lead to feeling more connection with human made landscape art, however only with the truthful human label and, interestingly, with the pixel art made by humans with the misleading computer label. This might again be viewed under the theory by Szubielska et al. (2020), that this information provides a frame of context under which the art can be understood better. Similar to findings by Bloom & Markson (1995), this information might lead to a shift of evaluation criteria, so that people were able to feel more connection with the ambiguous pixel art with the context of it being computer generated than it being created by a human artist.

All these correlations can be viewed as more evidence that people were able to sense the original human artist through the artwork, because these correlations were not found for the art made with AI or the computer generated pixel pictures.

In general, people's openness to the concept of emotion transmission in art might be a factor that influences to which degree people feel emotion, a connection or emotion or perceive intentions through art and how much they understand or acknowledge these sensations. Future research might consider this factor in a more nuanced manner to study its impact on emotional connection in art appraisal.

5.3 Limitations and Future Research

Despite balancing some restraints of the study design mentioned by Demmer (2021), new limitations arose in our design that might be considered by future research in this field.

Even though we consciously omitted the valence of emotion felt by viewers and focussed on its intensity, collecting this facet of felt emotion would have led to more nuances and comparability in analysing the data, especially for comparing brain activity for positive and negative emotions and differentiating more between the representational and abstract art, as some viewers felt anger or annoyance towards the pixel art.

Moreover, some participants intentionally tried not to pay attention to the labels provided during the expectation period, as they wanted to focus solely on the viewing experience. Thus, emphasizing the expectation period or its importance for the research might have led to a more conclusive sample of brain activity. In accordance with this, the number of trials might have blurred the expectation period with the viewing period. Even longer viewing times for both the label and the viewing period might have provided more conclusive data.

Ambiguous findings stem from labelling art, which is especially true in the field of emotional responses to art. This connective aspect of art appraisal has been theorized as essential part of experiencing art, yet to our knowledge this is the first study exploring whether this emotional and empathic facet extends to the expectation period of art appraisal. While the fNIRS data collected in this study is a starting point, future research is needed to gain valuable and more detailed insight into this field. Both behavioural and neuronal studies on anticipation and emotions, especially focussing on the artist's humanness, are still scarce.

On a neuronal level, we suggest exploring a wider array of brain areas involved in art appraisal and emotional reactions to art as well as different imaging methods. This would gain more insight into how people prepare for an art experience and maybe on what people anticipate when they decide to enter an art exhibition. In the context of comparing complex representational art and abstract generative pixel art, including motor areas or reward areas as comparison to empathy or ToM areas might help to differentiate the anticipation and reaction to these contrasting art types.

Moreover, the openness to emotion transmission in art might be a promising factor to consider more detailed in future research, as this might moderate or impact to which extent viewers expect feeling emotion or connection to artworks before viewing them. Considering these factors will lead to further and more detailed insights into empathic expectation and anticipation of art.

To conclude, while we did not find neuronal evidence for an empathic anticipation of art, our results highlight the facets of connecting to the mind behind the artwork, especially in generative art. This project provides a first view into social and empathic preparation to viewing art and aims to encourage further research into this topic.

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Table of Figures

Table of Tables

Appendix

Abstract English

Expectation and anticipation shape and constitute many of our thoughts, interactions and everyday situations. Anticipation is also understood as a key factor for experiencing art, as people expect a rewarding experience which then impacts the assessment of the art. As empathy and a connection to the artist through the artwork have also been identified as crucial for experiencing art, the question arises whether people prepare for viewing art by anticipating an empathic connection or communication on a neuronal level. In our fNIRS study, we used highly similar computer generated art and art made by human artists with varying stimulus complexity, with varying levels of human input in the computer generated pictures, to investigate whether the proposed humanness of the artist (human or computer) influences the expectation of the experience. In addition to anticipation, we investigated the impact of labelling and picture type on the viewing experience, both behaviourally and on a neuronal level. While we did not find evidence for the activation of empathy when anticipating both human made and computer generated art, our results suggest that viewers were able to connect to all picture types, regardless of the label provided. This suggests that the perceived source of art is more important for the viewing experience than both the suggested and the actual source. These findings encourage further discussion on how computer generated art is understood both in the art world and in research concerning connective aspects of art.

Abstract German

Erwartung und Vorhersagen formen viele unserer Gedanken, Interaktionen und Alltagssituationen. Erwartung wird auch als Schlüsselfaktor um Kunst zu erleben verstanden, da Betrachter eine lohnende Erfahrung erwarten, was dann wiederum die Auseinandersetzung mit der Kunst beeinflusst. Da Empathie und eine Verbindung zum Künstler durch das Kunstwerk auch essentiell für das Kunsterleben sind, ergibt sich die Frage ob Betrachter sich auf neuronaler Ebene auf die Interaktion mit Kunst vorbereiten indem sie eine empathische Verbindung oder Kommunikation durch das Kunstwerk erwarten. In unserer fNIRS Studie haben wir ähnliche von menschlichen Künstlern erstellte und computergenerierte Kunst mit unterschiedlicher Stimuluskomplexität und variierenden Anteilen menschlichen Inputs bei den computergenerierten Bildern verwendet, um zu untersuchen, ob die vorgeschlagene Menschlichkeit des Künstlers (Mensch oder Computer) die Erwartung auf das Erlebnis beeinflusst. Zusätzlich zur Erwartung haben wir den Einfluss von Labelling und des Bildtypen auf das Kunsterleben sowohl auf Verhaltens- und auf neuronaler Ebene untersucht. Wir haben keine Hinweise auf verstärkte Empathieaktivierung in der Vorbereitung auf sowohl menschliche als auch computergenerierte Kunst gefunden, aber unsere Ergebnisse deuten darauf hin, dass Betrachter unabhängig vom Label eine Verbindung zu allen Bildtypen herstellen konnten. Das legt nahe, dass die wahrgenommene Quelle der Kunst wichtiger für das Kunsterleben ist als die vorgeschlagene und die echte Quelle. Diese Erkenntnisse regen weitere Auseinandersetzung damit an, wie computergenerierte Kunst sowohl in der Kunstwelt als auch in der Forschung im Kontext der Verbindung zwischen Künstler und Betrachter verstanden werden.

Tables

Table 10

Post Questionnaire: Statements regarding rating technique and thinking patterns

Statement	N
Rating these stimuli was difficultfor me.	15
I did not understand some of the questions.	2
I looked for patterns in the digital pictures.	30
Generally I decided that patterns in the digital artworks are indicators of a human artist.	7
The more random and chaotic the pixel pictures were, the more likely it was computer generated.	11
If I felt an emotion or intention while viewing, I thought that the picture was made by a human artist.	11
I answered the questions mostly randomly.	3
I was pretty confident about my ratings.	10
I was not able to tell most digital pictures apart.	11
I relied on my gut feeling whether the pictures were computer generated or made by a human artist.	25

Note: N = Number of people who agreed with the statement

Table 11

Post Questionnaire: Answers to the open questions - originally in German, translated to English

"Ich habe die Bilder beurteilt ob sie mich angesprochen haben oder nicht, unabhängig ob es computergeneriert ist oder nicht. Intentionen	"I judged the pictures whether they spoke to me or not, regardless whether they were computer generated or not. It was difficult to

habe ich schwer erkannt.!	recognize intentions!"
„Ich habe den Aussagen geglaubt, aber ich war teilweise sehr verwundert und erstaunt über die Zuordnung menschlich bzw. computergeneriert, habe den Wahrheitsgehalt aber nicht hinterfragt:"	„I believed the labels, but sometimes I was surprised and astonished about the assignment human or computer generated, but I didn't question the truth content."
„Farben und klare Formen die gefallen ließen die Bilder eher menschlich auf mich wirken."	„Likeable colours and clear shapes let the pictures seem more human to me."
„Es war schwer bei den Bildern von Mensch/Computern zu unterscheiden, da beide Optionen möglich wären (e.g. Computer generiert Muster und Mensch ‚Chaos' und vice versa). Mein Fokus war mehr auf der Frage, gefällt mir das Bild oder nicht."	„It was difficult to distinguish human/computer generated pictures because both options seem possible (e.g. computer generated pattern and human generated 'chaos' and vice versa. My focus was more on the question whether I like the picture or not."
„Die Pixelbilder sind nervig und schlecht, egal, ob sie von Mensch oder PC hergestellt sind. Die Zuordnungen habe ich immer geglaubt, bzw nicht in Frage gestellt."	„The pixel pictures were annoying and bad, regardless whether they were made by a human or computer generated. I always believed the labels, or didn't question them."
„Für mich war das Transportmedium ‚Bildschirm' schwierig, weil das Bild an sich dadurch schon verändert wird."	„For me the transport medium of monitor was difficult, because the picture itself is altered because of that."
„Die Bilder haben mich irgendwann begonnen zu ärgern – deshalb haben sie so etwas wie ‚Emotion' hervorgerufen."	„At some point, the pictures started to annoy me – that's why they elicited something like 'emotion'."
„Noch stärker als die Begründung ‚klare Formen und Konturen' sind das Sehen von Pinselstrich und anderen Malspuren (bei der Gemäldekunst). / Ich würde keines der Pixelbilder der Kategorie Kunst zuordnen (hatte deshalb eine großteils sehr indifferente Einstellung gegenüber der verschiedenen	„Even stronger than the reasoning 'clear shapes and contours' are visible brush strokes and other traces of the process (for the non-digital artworks). I would categorize none of the pixel pictures as art (that's why I mostly had an indifferent attitude towards the different pictures.) I would not be able to say/exclude

Bilder) / Ich könnte nicht mal sagen/ausschließen, ob sich eines der Pixelbilder wiederholt hat.“	whether one of the pixel pictures was repeated.”
„Gerade bei den Pixelbildern kann man meiner Meinung nach nicht feststellen, ob es computergeneriert oder von einem Menschen gemacht ist, sonst habe ich nach Bauchgefühl entschieden.“	„In my opinion, especially with the pixel pictures one can’t determine whether they are computer generated or made by a human, otherwise I relied on my gut feeling.”
„Ich habe versucht, die Beschreibungen zu ignorieren und mich eben darauf konzentriert, ob die Bilder in mir was auslösen.“	„I tried to ignore the labels and to concentrate on whether the pictures arouse something in me.”
„Pixelbilder können sowohl von Mensch oder Computer sein, ich konnte das nicht unterscheiden anhand der Anordnung der Pixel.“	„Pixel pixtures can be made by a human as well as computer generated, I couldn’t tell that apart relying on the arrangement of pixels.”
„Ich habe mich hauptsächlich auf mein Bauchgefühl verlassen – manche Pixelbilder kamen mir sehr ähnlich vor.“	„I mainly relied on my gut feeling – some pixel pictures seemed very similar to me.”
„Tendenziell geglaubt dass es computergeneriert ist“ (Pixelbilder)	„Tendentially I believed that the pixel pictures were computer generated.”
„Es waren – abgesehen von den Pixelbildern – ähnliche Bilder (viele verschwommene Berglandschaften).“	„The pictures were – except for the pixel pictures – similar pictures (many blurry mountain landscapes).”
„Ich habe den Beschreibungen geglaubt, war aber oft überrascht von ‚guten‘ computergenerierten Bildern.“	„I believed the labels, but was often surprised by ‘good’ computer generated pictures.”
„Rausch- /Streufunktionen“ (Pixelbilder)	„Noise/scattering functions” (pixel pictures)
„Ich habe bei den Pixelbildern nach einem Rhythmus gesucht, weniger nach einem Muster.“	„For the pixel pictures I looked more for a rhythm than for a pattern.”
„Bilder die deutliche Pinselstriche zeigen,	„Pictures showing brush strokes seem human.”

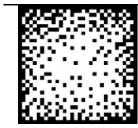
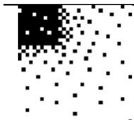
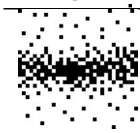
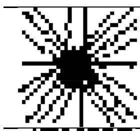
wirken menschlich.“	
„Bei sehr klaren Formen und Konturen habe ich der Beschreibung ‚menschlich‘ weniger geglaubt.“	„For very clear shapes and contours I believed the label ‘human’ less.”
„Viele Muster bzw. Wiederholungen in den Pixelbildern habe ich eher als computergeneriert ‚algorithmisch‘ wahrgenommen.“	„Many patterns or repetitions in the pixel pictures I perceived as more computer generated ‘algorithmic’.”
„Verschwommene Bilder haben mich stutzig gemacht.“	„Blurry pictures puzzled me.”
„Bei den Nicht-Pixelbildern bin ich mir rückblickend unsicher, ob ein Computer so etwas wirklich zustande bringen kann Andererseits dachte ich, wenn man ihm genug Vorlagen gibt, könnte es möglich sein. Ansonsten war ich mir aber in der Einschätzung recht sicher. Auf jeden Fall sehr spannend!“	„For the non-pixel pictures, in retrospective I’m uncertain whether a computer really is able to bring about something like this. On the other hand, I thought when one gives the computer enough templates, it could be possible. Otherwise, I was rather sure with my assessment. Anyway, very exciting!”
„Irgendwann ist mir aufgefallen, dass die Beschreibungen nicht immer schlüssig waren. Da habe ich begonnen bei jedem Bild zu hinterfragen, ob das jetzt computergeneriert ist oder nicht und konnte den Fokus nicht mehr so auf das Erleben beim Betrachten richten.“	„At some point I noticed that the labels were not always coherent. Then I started to question for every picture, whether it is computer generated or not and I couldn’t focus as much on the experience while viewing.“
„Alles geglaubt, Programmierung mittlerweile sehr fortgeschritten. Emotionsbewertung betraf oft ‚Ärger‘ bis ‚leichten‘ Ärger. Viele Bilder wurden mMn. Von Menschen, nicht von Künstlern gemacht.“	„Believed everything, programming is very advanced by now. Appraisal of emotions was often ‘anger’ to ‘slight anger’. In my opinion, many pictures were made by humans, not by artists.”
„Emotionsbewertung fiel mir schwer wegen Skalierung -> die meisten Pixelbilder haben	„I found appraisal of emotions difficult because of the scales -> most pixel pictures

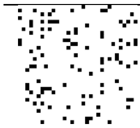
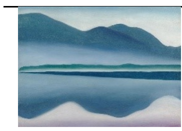
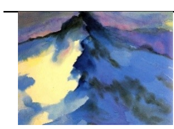
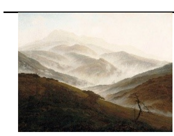
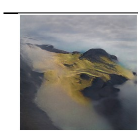
bei mir Genervtheit bewirkt und ich wüsste nicht wo dies einzuordnen wäre.“ („-> positive und negative Emotionen auf gleicher Skala“)	elicited annoyance in me and I don’t know at what this would classify.” (“-> positive and negative emotions on same scale”)
„Ich habe versucht, Argumente dafür/dagegen im Bild zu suchen, wenn die Beschreibung ‚menschlich‘ war.“	„I tried to look for arguments for/against in the picture, when the label was ‘human’.”
„Ich habe mich gefragt, ob die Pixelbilder von einem Menschen digital erstellt wurden und ob die Intention war es wie ein zufällig generiertes Bild aussehen zu lassen. Bei den ‚Gemälden‘ habe ich die Ränder/Oberfläche nach Farbrissen etc. abgesucht, die auf ein menschliches Bild hinweisen. Ich war allen Angaben erst mal skeptisch gegenüber, weil ich mir vorstellen kann, dass Computer schon gute Algorithmen haben können, die menschliche Kunst nachahmen.“	„I asked myself whether the pixel pictures were made by a human digitally and whether the intention was to make it look like a randomly generated picture. Regarding the ‘artworks’, I looked for tears in the paint on the surface/the edges that point to a human picture. At first, I was sceptical towards all labels, because I can imagine that computers already have good algorithms that mimic human art.”
„Bei den Pixelbildern habe ich mir gedacht, dass sie von Menschen am Computer ‚gezeichnet‘ wurden.“	„Regarding the pixel pictures, I believed that they were ‘drawn’ by humans sitting at a computer.”
„Ich habe mich gefragt, ob Computer Fotos zu einem ‚Bild‘ mit bestimmter Zeichenart verarbeiten können. Dann müssten sie nicht selbst ‚zeichnen‘ sondern nur reproduzieren.“	„I asked myself whether computers are able to process photos as a ‘picture’ with a certain style. Then they would not have to ‘draw’ by themselves, but just reproduce.”

Table 12

Complete List of Pictures used in the experiment

Picture	Picture Code	Source
	PixHum5	Demmer, 2021

	PixHum1	Demmer, 2021
	PixHum8	Demmer, 2021
	PixHum3	Demmer, 2021
	PixHum2	Demmer, 2021
	PixHum4	Demmer, 2021
	PixHum7	Demmer, 2021
	PixHum6	Demmer, 2021
	PixCP	Created with RNG (2021) w:b 1:1
	PixCP	Created with RNG (2021) w:b 1:1
	PixCP	Created with RNG (2021) white adjust 30
	PixCP	Created with RNG (2021) white adjust 40
	PixCP	Created with RNG (2021) w:b 1:1
	PixCP	Created with RNG (2021) w:b 1:1

	PixCP	Created with RNG (2021) white adjust 20
	PixCP	Created with RNG (2021) white adjust 40
	RepHum1	John Constable – The Stour (1810)
	RepHum7	Alexej von Jawlensky – Hill (1912)
	RepHum5	Giorgia O'Keeffe – Lake George (1922)
	RepHum8	William Turner – Laurenzer See with Schwyz and the Mythen (n.d.)
	RepHum4	Vincent van Gogh – Landscape with Canal (1885)
	RepHum2	Alexej von Jawlensky – Landscape in Oberstdorf (1912)
	RepHum6	Emil Nolde – Matterhorn (n.d.)
	RepHum3	Caspar David Friedrich – Riesengebirgslandschaft mit aufsteigendem Nebel (1810-20)
	AI6	Obvious – Kindness (2021)
	AI2	Obvious – Newness (2021)

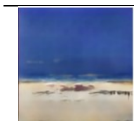
	AI8	Obvious – Love (2021)
	AI1	Obvious – Support (2021)
	AI3	Elgammal, 2017 – CAN
	AI7	Elgammal, 2017 – GAN
	AI5	Elgammal, 2017 – CAN
	AI4	Elgammal, 2017 – GAN

Table 13

Correlations between variables of pre-study and mPFC activity

Variable	1.	2.	3.	4.	5.	6.	7.	8.
1. mPFC	-							
2. QCAE_AE	-9.2e-24	-						
3. QCAE_CE	-6.6e-22	.58	-					
4. Previous Knowledge about AI Art	1.1e-22	-.11	-.1	-				

5. Openness to Emotion Transmission	1.5e-21	.57	.33	-.11	-			
6. Previous info about AI authorship	-2.9e-22	.32	.02	.21	-.05	-		
7. Previous Experience with Art	2.4e-21	.36	.19	.33	.41	-.11	-	
8. Control	-1.1e-22	-.14	.07	.44	.24	-.33	.45	-

Note: QCAE_AE = QCAE Factor Affective Empathy, QCAE_CE = QCAE Factor Cognitive Empathy, Control = Experience with and opinion on Art made by Children and Animals

Table 14

Correlations between variables of pre-study and lTPJ activity

Variable	1.	2.	3.	4.	5.	6.	7.	8.
1. lTPJ	-							
2. QCAE_AE	7.2e-22	-						
3. QCAE_CE	-3.1e-22	.58	-					
4. Previous Knowledge about AI Art	-2.5e-22	-.11	-.1	-				
5. Openness to Emotion Transmission	3.7e-22	.57	.33	-.11	-			

6. Previous info about AI authorship	-3.2e-23	.32	.02	.21	-.05	-		
7. Previous Experience with Art	6.8e-23	.36	.19	.33	.41	-.11	-	
8. Control	-2.1e-22	-.14	.07	.44	.24	-.33	.45	-

Note: QCAE_AE = QCAE Factor Affective Empathy, QCAE_CE = QCAE Factor Cognitive Empathy, Control = Experience with and opinion on Art made by Children and Animals

Table 15

Correlations between variables of pre-study and rIFG activity

Variable	1.	2.	3.	4.	5.	6.	7.	8.
1. rIFG	-							
2. QCAE_AE	-3e-24	-						
3. QCAE_CE	-6.7e-22	.58	-					
4. Previous Knowledge about AI Art	2.7e-22	-.11	-.1	-				
5. Openness to Emotion Transmission	5.5e-22	.57	.33	-.11	-			

6. Previous info about AI authorship	-5e-22	.32	.02	.21	-.05	-		
7. Previous Experience with Art	1.2e-21	.36	.19	.33	.41	-.11	-	
8. Control	4.3e-23	-.14	.07	.44	.24	-.33	.45	-

Note: QCAE_AE = QCAE Factor Affective Empathy, QCAE_CE = QCAE Factor Cognitive Empathy, Control = Experience with and opinion on Art made by Children and Animals

Table 16

Correlations between variables of pre-study and O1 activity

Variable	1.	2.	3.	4.	5.	6.	7.	8.
1. O1	-							
2. QCAE_AE	2.8e-22	-						
3. QCAE_CE	-5.9e-22	.58	-					
4. Previous Knowledge about AI Art	-3.1e-22	-.11	-.1	-				
5. Openness to Emotion Transmission	-6e-22	.57	.33	-.11	-			
6. Previous info about AI	4.6e-22	.32	.02	.21	-.05	-		

authorship								
7. Previous Experience with Art	1.6e-21	.36	.19	.33	.41	-.11	-	
8. Control	-1.7e-22	-.14	.07	.44	.24	-.33	.45	-

Note: QCAE_AE = QCAE Factor Affective Empathy, QCAE_CE = QCAE Factor Cognitive Empathy, Control = Experience with and opinion on Art made by Children and Animals

Figures

Figure 21

Mean Perceived Connection of each Participant per Picture Category

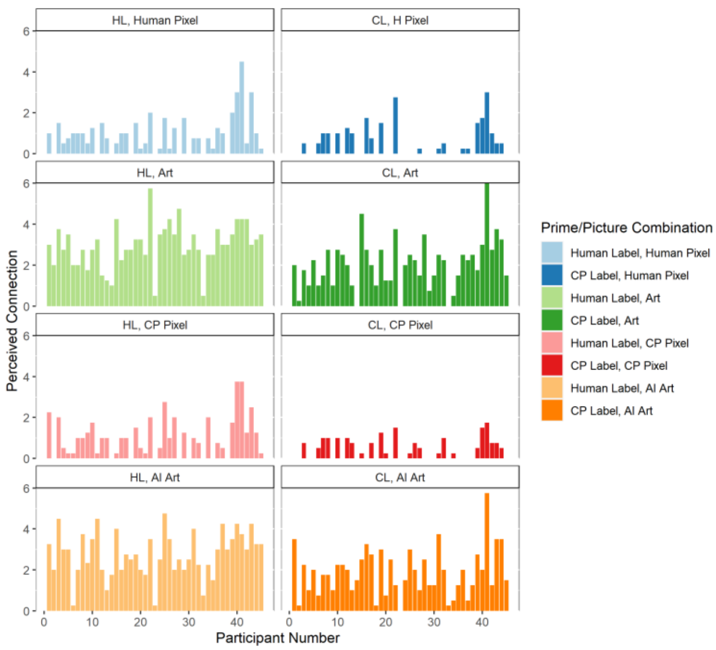


Figure 22

Mean Felt Emotion of each Participant per Picture Category

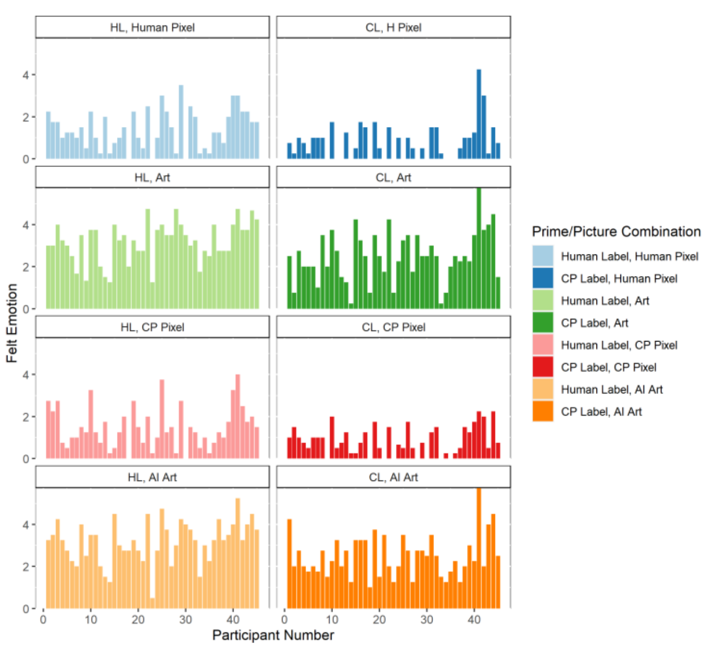


Figure 23

Mean Perceived Intention of each Participant per Picture Category