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An Investigation on the Influence of Extrinsic and Intrinsic Properties on Outcomes of the Aesthetic Experience

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An Investigation on the Influence of Extrinsic and Intrinsic Properties on Outcomes of the Aesthetic Experience

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Psychology
with a concentration in Cognitive Neuroscience

by

Christina Lee Chao

Dissertation Committee:
Associate Professor Emily D. Grossman, Chair
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2020

DEDICATION

To my family:
My Mom, Jimmy, Yi-yi, Kowfu, Poh-Poh, Gongh-Gongh, Kowmou, and Tommy

No one can take your knowledge away from you.
-My Mom

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VITA

Christina Lee Chao

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ABSTRACT OF THE DISSERTATION

An Investigation on the Influence of Extrinsic and Intrinsic Properties on Outcomes of the Aesthetic Experience

by

Christina Lee Chao

Doctor of Philosophy in Psychology

with a concentration in Cognitive Neuroscience

University of California, Irvine, 2020

Professor Emily D. Grossman, Chair

The study of empirical aesthetics is the systematic examination of the unique psychological experiences that arises when people explore and interact with art. Empirical aesthetics makes a distinction between the extrinsic properties of art, those things inherent to the art piece such as its physical features, and the intrinsic properties of the viewer, such as a person's expertise or traits that contribute to individual differences when viewing the art piece. This dissertation reports on three experiments that evaluate how extrinsic and intrinsic properties influence attention on art and how people evaluate perceive complexity of and preference for art. Experiment 1 investigates how blur implementation affected the distribution of attention on visual art through a change blindness task. The results show that blur implementation boosts the saliency of areas of interest (AOIs) only when applied liberally everywhere on the art piece except the AOI. Experiment 2 examines how well salience models can predict the locations of human eye fixations and scanpaths. The results suggest that people tend to use extrinsic properties more often to guide their attention across an art piece for the assumed first viewing. Human scanpaths were more

similar to each other compared to what previous studies had reported for repeated viewings of an art piece. Additionally, salience model scanpaths were less similar than those obtained from observers, indicating that they do not weight the relative salience of regions the same as humans. Experiment 3 investigates how an individual's Autism Quotient (AQ) affects evaluations of perceived complexity and preference. Although we found little influence of AQ level on these measures, the results suggest that it may be possible to explain earlier, contradictory result relating complexity to preferences using a set-point model. These three experiments show the complexities of how extrinsic and intrinsic properties can influence difference outcomes of the aesthetic experience. The aesthetic experience is not simply affected only by extrinsic properties or intrinsic properties alone – the interaction of these properties creates the unique experience people have when they view art.

CHAPTER 1: INTRODUCTION

Art comes in many forms and we can view art pieces in different ways. What grabs our attention when we look at an art piece? What do we actually seek out in an art piece? Why do we connect with certain art pieces and not others? How do we interpret its meaning? Additionally, how do we evaluate these pieces to say we "prefer" or that we "like" some art pieces as opposed to other art pieces? Is it because of what is on the art piece or how the art piece has been arranged? Is it because of different traits we possess that affect how we perceive art pieces that influence our preferences? These questions point out the different ways we can interact with art and the different things that contribute to how we interact with art: in short the aesthetic experience.

The aesthetic experience is a unique psychological experience tied to the perception of and interaction with art; this experience is generally reduced by researchers to the study specific sensory, perceptual, and cognitive processes that are said to make up the aesthetic experience (Bao et al., 2017; Berleant, 2000; Biaggio & Supplee, 1983; Carbon, 2018; Cupchik & Winston, 1996; Jacobsen, 2006; Marković, 2012; Palmer et al., 2013). There are two main approaches to studying the aesthetic experience: empirical aesthetics and neuroaesthetics. Empirical aesthetics seeks to observe physical behaviors and measure how individuals evaluate art pieces on different scales such as beauty or preference in the aesthetic experience (Augustin & Wagemans, 2012; N. Bullot, 2012; Carbon, 2018; Chatterjee et al., 2010; Cupchik & Winston, 1996; Mainwaring, 1941; Palmer et al., 2013). On the other hand, neuroaesthetics primarily seeks to measure brain activity related to aesthetic experiences such as free viewing art or evaluations of the preference or the beauty of an art piece (Chatterjee, 2010; Chatterjee & Vartanian, 2014; Cinzia & Vittorio, 2009; Manuela Maria Marin, 2015; Nadal et al., 2012; Pearce et al., 2016; Zeki, 1998, 2002). These approaches share some common threads including how they both must deal with two main elements in the aesthetic experience: the art piece and the person viewing the art piece.

1.1 EXTRINSIC & INTRINSIC PROPERTIES

Many questions about the aesthetic experience involve two important properties: the characteristics of the art piece and the characteristics of the person looking at the art piece. Let's label the characteristics of the art piece as extrinsic properties of the aesthetic experience and the characteristics of the person as intrinsic properties. Approaches to studying the aesthetic experience attempt to tackle aspects of the big question: what extrinsic and intrinsic properties affect how a person interacts with the art piece?

Extrinsic properties are the things inherent to the art piece itself as it was created by an artist with techniques and elements integrated to become a 2-D art piece that influence how the audience will look at and explore the art piece. The artist has their own intentions and understands principles that affect human perception; thus, they utilize techniques that will convey their personal intentions on how they want their art piece to appear to viewers (Arnheim, 1965; Cavanagh, 2005; Conway & Livingstone, 2007; Livingstone & Hubel, 2008; McManus et al., 2011). On the resulting 2-D art piece, there are perceptual features created by the artist that can drive and influence how individuals explore and evaluate the piece. Studies have shown how some of these perceptual features influence exploration and evaluation of a piece; for example, how color influences preference for an art piece (Massaro et al., 2012). Other research has observed artistic principles such as symmetry versus asymmetry and composition of elements via the rule of thirds and their effects on perception and aesthetic evaluations such as symmetry versus asymmetry and composition of elements via the rule of thirds (Amirshahi et al., 2014; Palmer et al., 2013; Sammartino & Palmer, n.d.; Svobodova et al., 2014).

Additionally, intrinsic properties are individual differences between persons who view an art piece that can also influence our behaviors directed at an art piece such as how we explore and evaluate art pieces. These individual differences can include traits and the type of expertise a person has. Studies have shown that individual differences do influence the different outcomes of the aesthetic experience; for example, personality traits on the openness scale influences preference for abstract art pieces (Feist & Brady, 2004; Furnham & Walker, 2001; Silvia & Nusbaum, 2011). Additionally, other research has shown how individual difference such as art expertise and even cultural background can influence how a person explores a visual stimulus (Boland et al., 2008; Chua et al., 2005; Masuda & Nisbett, 2006; Miyamoto et al., 2006; Pihko et al., 2011).

Although extrinsic and intrinsic properties are important in the aesthetic experience, researchers must pick specific dependent variables to measure. This choice affects which properties of the aesthetic experience can be studied.

1.2 APPROACHES

Research on the different aspects of the aesthetic experience can be categorized into two approaches: empirical aesthetics and neuroaesthetics. Both approaches seek to understand the different processes involved in the aesthetic experience, but they focus on different dependent variables and measurements of behavior. As noted earlier, a variety of questions can be asked about the aesthetic experience generally and, more specifically, the outcomes that a person may exhibit from viewing an art piece. Some of those outcomes can be measured directly, such as the sequence of eye movements produced when a person explores an art piece or the brain activity that occurs while a person is looking at the art piece. Other outcomes are inherently subjective, such as how a person evaluates the art piece or whether they prefer that art piece over another one.

Empirical aesthetics seeks to understand the relationship between the art piece, individual differences, and specific psychological and behavioral processes of the viewer in the aesthetic experience. Neuroaesthetics, on the other hand, seeks to map out specific brain areas and neural networks of the different perceptual and cognitive processes involved in the aesthetic experience (Chatterjee, 2010; Chatterjee & Vartanian, 2014; Pearce et al., 2016; Zeki, 1998, 2002). However, even though these two approaches have different priorities, they both attempt to observe both extrinsic and intrinsic properties and how these properties affect the different outcomes they measure in order to understand the underlying processes of the aesthetic experience.

Empirical Aesthetics

Empirical aesthetics focuses on measurements of outcomes that a person may exhibit when viewing an art piece such as evaluation of beauty, preference, emotional state. Additionally, empirical aesthetics also seeks to measure physical behaviors such as how a person explores an art piece through methods such as eye tracking of where their eye fixations fall on the art piece (Kesner et al., 2018; Massaro et al., 2012; Quian Quiroga & Pedreira, 2011; Rosenberg & Klein, 2015; Villani et al., 2015; Walker et al., 2017). Many empirical aesthetic studies focus on only one outcome or one specific dependent variable to understand the processes involved in the aesthetic experience. For example, evaluations of "beauty" provide a common measurement of behavior in empirical aesthetics where researchers ask participants to look at an art piece and rate how much they find the art piece to be beautiful on a Likert scale (Forsythe et al., 2011; Massaro et al., 2012; Nadal et al., 2010). As researchers measure variables such as beauty evaluations, they also observe what factors can affect those evaluations such as perceptual features of the art piece or the traits a person possesses – the extrinsic and intrinsic properties of the aesthetic experience (Belke et al., 2010; Farley & Ahn, 1973; Farley & Weinstock, 1980; Feist & Brady, 2004; Furnham & Walker, 2001).

Neuroaesthetics

Neuroaesthetics primarily focuses on linking brain areas to the different perceptual and cognitive processes of the aesthetic experience through neuroimaging techniques including fMRI and EEG. This approach characterizes the aesthetic experience through functional areas of the brain that are active when an individual views an art piece (Chatterjee, 2010; Chatterjee & Vartanian, 2014; Cinzia & Vittorio, 2009; Nadal et al., 2012; Pearce et al., 2016; Zeki, 2002, 2002). For example, the aesthetic triad model maps out three components with their correlating functional areas to define the aesthetic experience: the emotional experience, perceptual processing, and cognitive processing (Chatterjee & Vartanian, 2014). Some other neuroaesthetic studies observe brain areas tied to individual differences in outcomes; for example, researchers have observed brain areas that become active when a person finds an art piece to be beautiful, and the art pieces that are rated to beautiful are different between subjects (Cela-Conde et al., 2004; Di Dio et al., 2007; Kawabata & Zeki, 2004).

1.3 MODELS

We turn now to three classes of models that incorporate data from both the empirical and the neuroaesthetic approach and attempt to explain the links between extrinsic and intrinsic properties to these outcomes.

Hedonic and Emotion Models

Hedonic models have looked at physical properties of an image and measured the "aesthetic pleasure" and arousal that arises from the image (D. E. Berlyne, 1972; Martindale, 1984). Specifically, hedonic models emphasize an ideal point that exists for a stimulus feature, and at that ideal point is where a viewer will say that stimulus is the most pleasurable to look at. Previous studies have explored how measures such as preference vary with different features such as perceptual complexity and ask whether there is an ideal point that most people will say is the most preferred or the most beautiful to look at (Daniel E. Berlyne, 1970; A. Forsythe et al., 2011; Nadal et al., 2010). However, these hedonic models don't fully capture how intrinsic properties may lead to unexpected outcomes; or example, in studies that looked at expertise and preference, participants that had more art expertise preferred simpler stimuli and nonexperts preferred more challenging stimuli (Belke et al., 2010; Muth et al., 2015).

Building on hedonic models of the aesthetic experience, emotional models emphasize emotional appraisals and arousal when evaluating art pieces where they observe "aesthetic emotions" such as interest and pleasure (Silvia, 2005, 2006). Emotional models emphasize the variety of emotions that can arise from cognitive processes involved in how viewers interpret the stimulus where emotions of disgust, anger, sadness, surprise, and interest are observed as well (Kuchinke et al., 2009; Menninghaus et al., 2017; Silvia, 2009; Silvia & Nusbaum, 2011). These emotional models are emphasized in the neuroaesthetic approach towards understanding the aesthetic experience where brain areas associated with different expressed emotions are mapped for a person looking at an art piece. Additionally, these emotional models try to tie in how we may interpret the semantic meaning of the art piece by observing individual differences in experiences and traits and how these differences influence the emotional states that arise in the aesthetic experience.

Fluency Model

The Fluency Model considers how individual differences and previous experiences make it easier to process the extrinsic properties of an art piece as a stimulus so that the piece becomes more preferable or likable (N. J. Bullot & Reber, 2013; Reber et al., 2004). Unlike hedonic models and emotional models, the fluency model primarily focuses on preference and liking evaluations that are considered to be part of the aesthetic experience, and this model tries to explain how these preferences are affected by both extrinsic properties such as composition and intrinsic properties such as expertise and familiarity. Studies have shown that familiarity and prototypicality can make stimuli more preferable (Hekkert & van Wieringen, 1996; Tuch et al., 2009). Some studies have shown that experts have different preferences than novices where art experts rated complex stimuli to be more beautiful or preferable (Millis, 2001; van Paasschen et al., 2015). The finding from these studies can be explained through the fluency model in which expertise is an intrinsic property that makes it easier to process complex things and, thus, more likable. However, there are studies that don't seem to follow this logic as previously mentioned; some studies have shown opposing results in which experts show more preference to simpler stimuli (Belke et al., 2010; Muth et al., 2015). So, the fluency model, like other aesthetic experience models, doesn't quite capture every phenomenon we observe for the aesthetic experience.

Perceptual Cognitive Models

Recent models emphasize more on the bottom-up and top-down processes of perception and cognition that make up the aesthetic experience. Leder et al., (2004) proposed a hierarchical model that emphasizes how perceptual features, attention, memory, and individual differences of expertise and previous knowledge modulates a viewers' affect over time as they view an art piece. Additionally, this model emphasizes cognitive processes such as interpretation of the art piece and how it may modulate perceptual processes to produce judgements such as preference for the art piece. Similarly, Redies (2015) proposed a similar model of aesthetics that, however, emphasized parallel processing of perception and cognition and how these processes modulate each other and build up to the aesthetic experience where the aesthetic experience is defined as the evaluations that occur on to the art piece. The difference between these two models is the way in which bottom-up and top-down processes are organized that lead to the aesthetic experience.

These perceptual cognitive models attempt to quantify extrinsic and intrinsic properties and how they influence one another to lead to a specific outcome in the aesthetic experience. Studies in both approaches of empirical aesthetics and neuroaesthetics show some support for these models as well. For example, in neuroaesthetic approaches, researchers have observed how bottom-up and top-down processes are modulated when viewing different art pieces (Fairhall & Ishai, 2008). Depending on the type of art piece (representational, intermediate, and abstract), researchers would have observed more brain activity in brain areas previously implicated in either bottom-up processing of attention versus top-down. Other studies have also observed how individual differences of familiarity with different art pieces led to activation of brain areas previously associated with more top-down processing of attention (Kim & Blake, 2010). In empirical aesthetic approaches, researchers observe how differences in intrinsic properties such as art expertise and extrinsic properties such as color or composition can modulate behaviors such as eye gaze and attention on an art piece (Francuz et al., 2018; Glazek & Weisberg, 2010; Nodine et al., 1993; Pihko et al., 2011; Quian Quiroga & Pedreira, 2011; van Paasschen et al., 2015).

1.4 SPECIFIC AIMS

Even though these models of aesthetics emphasize different outcomes, these outcomes all pertain to either the extrinsic properties of the art piece itself or the intrinsic properties of the observer/participant. The extrinsic/intrinsic distinction also cuts across both approaches to research on aesthetics.

The models we have discussed provide different ways to explain how specific intrinsic and extrinsic properties affect some outcomes. However, because these models focus on different aspects of the full aesthetic experience, none has yet fully encompassed the processes that make the aesthetic experience so vast and complex. Current studies take the approach of highlighting a few specific intrinsic and extrinsic properties out of the many that exist and study how these properties influence a certain outcome of the aesthetic experience.

This dissertation includes three experiments that use an empirical approach to look at how intrinsic and extrinsic properties relate to the evaluation of art pieces. Experiment 1 examines how an extrinsic property, blur, is used as a perceptual element to guide attention. Additionally, this experiment seeks to observe whether art expertise, an intrinsic property, influences how blur guides attention within an art piece. Experiment 2 will compare the human eye-tracking data on an art piece with the outputs of visual salience models to identify regions of where people tend to look and whether salience models can capture the same regions on stimuli such as art pieces. Lastly, Experiment 3 focuses on how traits related to individuals with Autism called the Autism Quotient may influence perceptual judgments of visual complexity and preference rankings.

CHAPTER 2: EXPERIMENT 1

Blur and Attention

2.1 INTRODUCTION

Artists are trained to use specific techniques to convey a desired aesthetic when creating an art piece. These techniques include lighting, balance and perspective, and local features such as highlights, shadows, and motion lines (Cavanagh, 2005; Conway & Livingstone, 2007; Livingstone & Hubel, 2008). Together, these factors shape the overall composition and aesthetics of the piece, the perceived complexity of the work, the process with which the art can be evaluated, and the extent to which the content conforms to prototypical norms (D. E. Berlyne, 1972; Martindale, 1984; Palmer et al., 2013; Reber et al., 2004).

In previous studies, researchers have evaluated the importance of texture and clarity by adding blur to localized areas of art pieces in controlled and balanced stimulus manipulations. In these studies, using both photography and representational art pieces, blurred areas are fixated less frequently and with later onset as compared to regions of clarity (unless the observer is explicitly instructed to seek regions of blur; (DiPaola et al., 2013; Enns & MacDonald, 2013; Latif et al., 2014; Smith & Tadmor, 2013). Indeed, the unique information carried by high and low spatial frequency content in art pieces can have dramatic impact on how ambiguous elements of the works are interpreted (Mamassian, 2008). From these findings, we conclude that blur as a texture element can direct spatial attention and that artists can guide viewer's attention through the strategic use of blur in complex representational art pieces.

What remains unclear is whether blur as a highlight, when applied consistent with artistic principles, will enhance the salience of the surrounded objects. In this investigation, we evaluate perceptual salience of items highlighted by blur, inserted such that it honors object boundaries and avoids disembodying the object from its surrounding context (e.g. separating a head from its body). The implementation of blur consistent with these principles is an important factor in preserving and enhancing the visual aesthetic while retaining the compositional balance of complex art pieces (Bhattacharya et al., 2010; Quian Quiroga & Pedreira, 2011).

We hypothesize that blur surrounding an object promotes its salience by creating a local area of texture contrast, a cue to guide attention to the highlighted object. To evaluate this, we use the change detection paradigm (alternating brief exposures to the original and altered versions of the image) as an indirect measure of object salience, comparing accuracy in detecting changes applied to items that are or are not "enhanced" by surrounding blur. Faces have been shown to be very salient in previous studies, so we will also identify areas of interests that are faces within art pieces (Cerf et al., 2008; New et al., 2007; Yarbus, 1967). We hypothesize that blur may most strongly modulate attention directed to items of relatively low salience, in which blur interacts with the salience associated with a region in an art piece given that highly salient regions (e.g. faces) may not benefit from added contextual elements to draw attention to them (e.g. a ceiling effect).

In Experiment 1A, we identify areas of interests (AOIs) within representational visual art pieces that will be altered for the blur manipulation in the change blindness procedure for Experiments 1B and 1C. In Experiments 1B and 1C, we measure sensitivity to changed areas when highlighted by blur locally or globally, respectively. All three parts of

Experiment 1 tested separate groups of participants, and no individual saw the same art piece twice. All art pieces included in these experiments were acquired through the website deviantArt, with express permission of the artist for usage in this research.

2.2 EXPERIMENT 1A: IDENTIFYING SALIENT AREAS OF INTEREST (AOIs)

In Experiment 1, we quantified the relative salience of areas in the art pieces through explicit (mouse clicks) and implicit (eye gaze) measures of attention. These measures were then used to isolate areas of interest (AOIs) in each art piece to be used in the subsequent change detection experiments (Experiments 1B and 1C).

Methods

Participants:

Twenty-nine individuals (4 males, 24 females, 1 preferred not to state) participated in the mouse click task in Experiment 1A. A different group of sixteen individuals (6 male, 10 female) participated in eyetracking component in Experiment 1A. All had normal or corrected to normal vision, were not colorblind (as indicated by self-report) and gave verbal informed consent approved by the University of California, Irvine IRB. All participants received course credit for their participation.

Stimuli:

Stimuli consisted of sixty-eight 2-D representational art pieces with clearly defined objects and figures, shown in the original colors and with no blur added (i.e. in the original format). Theses art pieces were gathered from 32 artists off of deviantart with their expressed permission. Each artist had at least 2 art pieces chosen to be a part of the stimulus set in this experiment. In the mouse clicking task, art pieces were scaled (preserving the original aspect ratio) such that the longest dimension subtended 16 degrees of visual angle, viewed at a distance of 58 cm. In the eye tracking experiment, art pieces were presented slightly larger (the longest dimension viewed as 24 degrees of visual angle). All aspects of the experiment were conducted using MATLAB with the PsychophysicsToolBox 3.11 (Brainard, 1997; Pelli, 1997).

Procedure:

Each individual viewed a pseudo-random selection of 34 art pieces out of a possible 68 such that each participant saw at least one art piece from each of the 32 artists. Viewing order of the subset of art pieces was randomized. Each art piece was displayed alone in an interactive window on which individuals had to indicate (with a slider) their sense of familiarity with the piece by answering "How familiar are you with this art piece?", and their sense of portrayed depth ("How far can you see out into the horizon in the 2-D image?"). Individuals were then asked to indicate by selecting a yes/no radio button whether the art piece conveyed clear depth segregation ("Does the art piece have a clear foreground background separation?") and a sense of motion ("Is there motion being portrayed in the art piece?"). Familiarity ratings were used to discard images that evoked a sense of past exposure, which we hypothesized may elicit altered patterns of attentive exploration (Zajonc, 1968). The questions regarding perceived depth and motion were included for subsequent experimental investigations and will not be discussed further in this analysis.

Following the rating questions, individuals were instructed to "Click on the things in the image that stand out to you. You may click multiple times." Participants had the option to click as many regions in the image as they preferred but were required to click on at least once before moving on to the next art piece. Individuals rated and clicked at their own pace, and so they could move freely back and forth between the art pieces long as they had already answered all the rating questions and had clicked at least once on the art piece.

Eyetracking data was collected using an Eyelink II (SR Research Ltd) controlled by a Dell Optiplex 755 PC in conjunction with MATLAB (version R2009a). Participants were positioned 23 inches from the monitor, with their chins stabilized using a headrest, and completed a standard 9-point calibration prior to the initiation of the experiment. All participants viewed each of the 68 art pieces for a minimum of five seconds, with no direct instructions or characterizations required (free viewing). This was a separate task from the "Explicit characterization of art pieces" with a different set of participants. Observers were instructed to press the spacebar when they were finished inspecting the images. Viewing order of the images was randomized.

Eye movement data were segmented by Eyelink II into fixation and non-fixation intervals, and the timing and duration of these fixations analyzed in Matlab. Fixations offscreen (less than 2% of the total) were excluded. On the basis of previous literature, image masks were created where face areas were identified in the sixty-eight art pieces. We then calculated the proportion of trials in which observers first fixated within the face region, the proportion of all fixations within the face relative to the total number of fixations (measured for that participant and that art piece), and the proportion of total viewing duration within the face region. These measures were compared for the face regions versus the remaining areas of the piece.

Results and Discussion

Explicit ratings:

On average, individuals identified 4.6 (st. dev. 2.10) salient regions per image, as revealed by the positions of the clicks. The distribution of clicks revealed areas on the art piece that participants deemed salient. Although faces subtended a relatively small visual area of these complex art pieces, participants tended to click on faces within the art pieces first and more often than other regions of the image. We found 58.9% (st. dev. 5.87) of the first clicks from each individual were on a face in the image, whereas 41.1% of the first clicks were on other regions of the image (Figure 1.1a). The total number of clicks on faces was significantly higher than for non-face regions on the first click ($t(28) = 2.78$; $p < 0.05$).

Eye tracking:

On average, individuals made 19.3 ($SD = 3.21$) fixations per art piece. Individuals tended to fixate on faces first and more frequently than any other region of the art pieces (Figure 1.1b). Approximately 74.1% ($SD = 3.30$) of the first fixations landed on a face while 25.9% landed on other regions in the art pieces, a statistically higher incidence of first clicks on the faces ($t(15) = 29.15$, $p<0.05$). Approximately 49.7% of the total fixations were directed to faces, while 50.3% of fixations were distributed elsewhere in the art pieces (Figure 1B). On average individuals spent the same amount of time gazing at faces as the combined total fixation duration across the remainder of the image. That faces are perceptually salient and attract directed eye gaze in the exploration of complex scenes is well known (Cerf et al., 2008; New et al., 2007; Yarbus, 1967). Our explicit and implicit measures show evidence that faces are salient which is consistent findings from previous works.

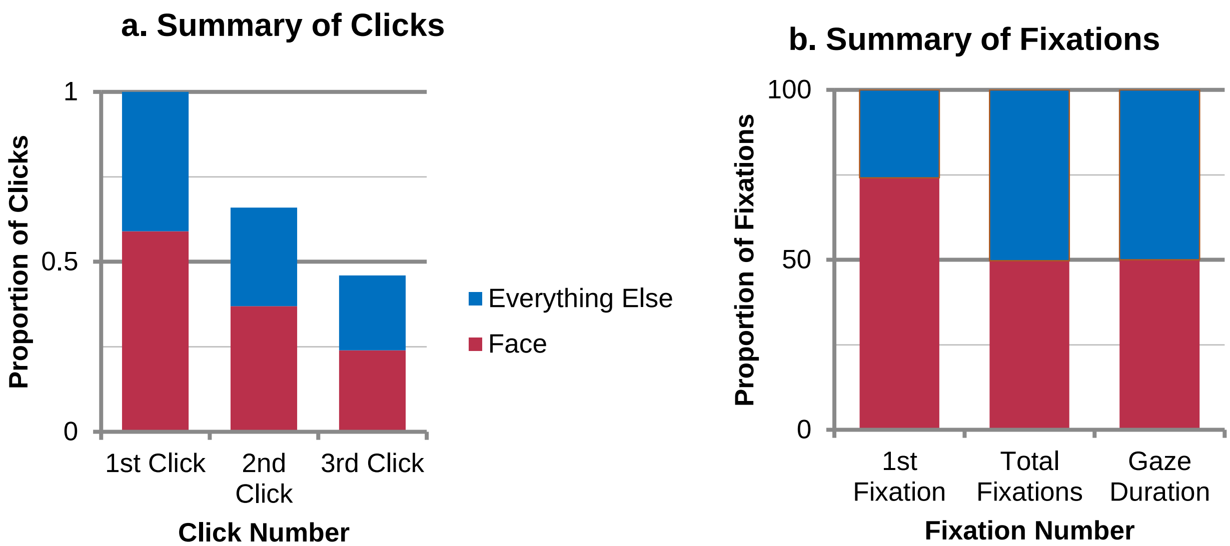

Figure 1.1: a. The distribution of the first three items identified by individuals as "important" in the explicit measure of salience. Participants clicked on faces in the art pieces most frequently and disproportionately among the first, second and third clicks (participants could freely identify as many items as they preferred and were required to select one region at a minimum).

b. Eye-tracking revealed that on the first fixation, approximately 74.08% of fixations fell on a face. Participants overall made half of their total fixations on faces versus elsewhere on the art pieces, with approximately half the gaze time allocated to faces versus other areas of the art piece.

From these results we isolated three areas of interest to be targeted in the change blindness experiments: The primary face (the most clicked and gazed upon face, human or nonhuman), the secondary face (if present in the art piece, identified as the second most frequently identified face), and a highly salient object that is not a face but was frequently identified by the participants. These regions are used in Experiments 2 and 3 as targets for change detection, with the goal of evaluating the impact of artistically manipulated blur on attentive selection.

2.3 EXPERIMENT 1B: CHANGE DETECTION AND ARTISTIC USES OF BLUR

To evaluate the potential of artistically manipulated blur as a highlight to promote perceptual salience, we measured the ability of observers to detect changes imposed on the selected area of interests (AOIs). AOIs were selected from the results of Experiment 1. Blur, at two levels of intensity, was applied to be consistent (surrounding the target) or inconsistent (superimposed on the target or surrounding a random region) with artistic principles that aim to draw attention to areas of interest. Accuracy for detecting the imposed change was subjected to an analysis of variance to evaluate the influence of blur implementation on object salience.

Methods

Participants:

Experiment 1B included 81 individuals (69 females, 12 males) in the low-intensity blur condition, and 59 individuals (46 females, 12 males, 1 preferred not to state) in the high-intensity blur condition. The number of subjects varied between the two groups because recruitment remained open in the low intensity condition in efforts to raise the population of individuals with self-reported artistic training. Ten of the individuals in the low-intensity blur condition self-reported as artists on a two-question questionnaire given to them prior to participating in the experimental task ("Are you a visual artist?", "Do you have experience critiquing art?"). Eighteen participants in the high-intensity blur condition self-reported as artists. All human individuals were recruited from the UCI Human Subject Pool, received course credit for their participation, and none had participated in Experiment 1A. All had normal or corrected to normal vision, were not colorblind (as indicated by self-report) and gave verbal informed consent approved by the University of California, Irvine IRB.

Stimuli:

Fifty-two of the original 68 art pieces were used for Experiment 2. Sixteen art pieces were eliminated based on higher familiarity ratings among the participants in Experiment 1A. Art pieces were scaled (preserving aspect ratio) to be displayed at 23 degrees of visual angle at the longest dimension, viewed at a distance of 58 cm.

In this change blindness experiment, we created an altered version of each image to include a color change that individuals were instructed to detect. The color changes were implemented using Photoshop to switch the hue, but maintaining the luminance, of the targeted item to its complementary color. The color change was restricted to object boundaries and to extend approximately 6-8 degrees of visual angle (220-250 pixel height; Figure 1.2). Four areas of interest were targeted for the color change: the main face, a secondary face (if present and also deemed salient), a salient object, and a non-salient object (an item that was not frequently clicked in the rating experiment).

Each image had one element selected for blur in one of the following three implementations: Blur Surround (locally), in which the blur was positioned around the targeted object and confined to approximately 6 degrees of visual area surrounding the object; Blur On, in which the blur was positioned over the targeted object in a circular shape with a diameter of 250-280 pixels (8-10 degrees of visual angle); Blur Random, in which the blur was positioned far from the targeted object and constrained within a central region with boundaries defined by the most eccentric click for that particular art piece so that the blur wouldn't end up too close to the borders of the art piece. In a fourth condition (Original) individuals viewed the images without any included blur. The blur was inserted using the Photoshop Gaussian filter tool, with a 2.5 pixel sigma full-width at half-magnitude (FWHM) bleed intensity in the low blur intensity condition, and 8.8 pixel sigma FWHM in the high blur intensity condition. The edges of the blur were smoothed (feathered option in Photoshop) to eliminate harsh edges (Figure 1.2).

The experiment proceeded as a 4x4 factorial design that varied the implementation of blur and the area of interest, for a total of sixteen unique conditions. To eliminate any impact of familiarity on change blindness accuracy, no individual saw the same art piece twice and thus this experiment proceeded as a between-individuals design.

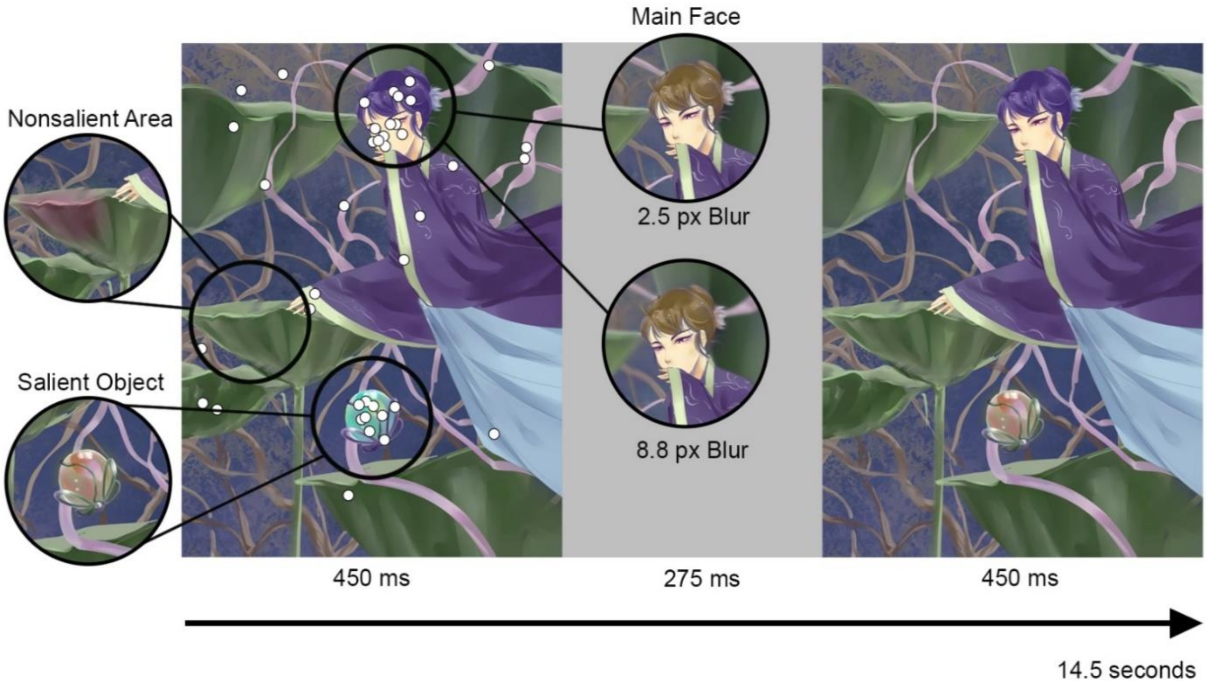

Figure 1.2: A sample art piece illustrating the distribution of clicks (white circles) made by 11 participants in a pilot of experiment 1A. Regions targeted for the change detection task for this image are encircled in black and enlarged. The original art piece and the changed art piece were displayed alternately for 450ms, with an interleaving 275ms blank, for a total trial time of 14.5 seconds. Change detection was implemented as a switch to the complementary hue in Photoshop, shown here as the change in hair color surrounding the main face. Blur implementation in the enlarged main face is the Blur Surround condition, with the Gaussian blur surrounding the region of interest without disembodying it. The trial shown on the timeline is an Original condition (no blur added).

Procedure:

Participants sat 58 cm away from the monitor with their heads positioned on a chin rest for stability. Individuals were shown a single art piece alternating with the changed version, with each image displayed for 450 ms and separated by a 275 ms blank interval. This sequence repeated for 10 iterations, for a total maximum trial time of 14.5 seconds (Figure 1.2). The participant was instructed to push any button on the buttonbox (Empirisoft Corporation) when they detected a change, then indicated using a mouse where the change occurred. If they did not see a change, they were instructed to not push the button and let the trial time out. They were not given feedback for their responses.

We computed accuracy and reaction time for detecting the color changes. These two measures yielded the same statistically significant findings, and thus here we report only the percent change detected accurratly. Statistics were computed in SPSS (IBM). Degrees of freedom were adjusted using the Greenhouse-Geisser correction in the instances for which violations of sphericity were detected using Mauchly's Test of Sphericity.

Results and Discussion

Figure 1.3 shows the group results for change detection accuracy across the sixteen conditions, shown separately for the high and low intensity blur conditions. A two-way repeated measures ANOVA of accuracy revealed a main effect of AOI in both the low-intensity blur ($F(2.62, 209.28) = 82.88$, $p<0.05$) and the high-intensity blur ($F(3, 174) = 56.37$, $p<0.05$) conditions. Post hoc comparisons revealed that individuals more accurately detected changes applied to the main face, secondary face, and salient object as compared to the non-salient object for both the low-intensity blur and high-intensity blur.

We found a main effect of blur implementation in the high intensity blur condition ($F(3, 174) = 5.09$, $p<0.05$), but not the low intensity blur condition ($F(3, 240) = 1.63$, $p=0.18$). Post hoc comparisons showed that when blur was applied with high intensity, change detection was most difficult when it was inserted in a random location away from the changed object (to be detected) as compared to when the art pieces were left in their original form (without blur), or when blur was applied on or surrounding the changed item (see the right panel of Figure 1.3).

We found no interaction between AOI and blur implementation in either low-intensity blur condition (F(8.37, 669.27) = 1.62, p=0.11) or the high-intensity blur condition (F(9, 522) = 1.57, p=0.12). The impact of the random blur position on detection accuracy did not depend on how the blur was implemented.

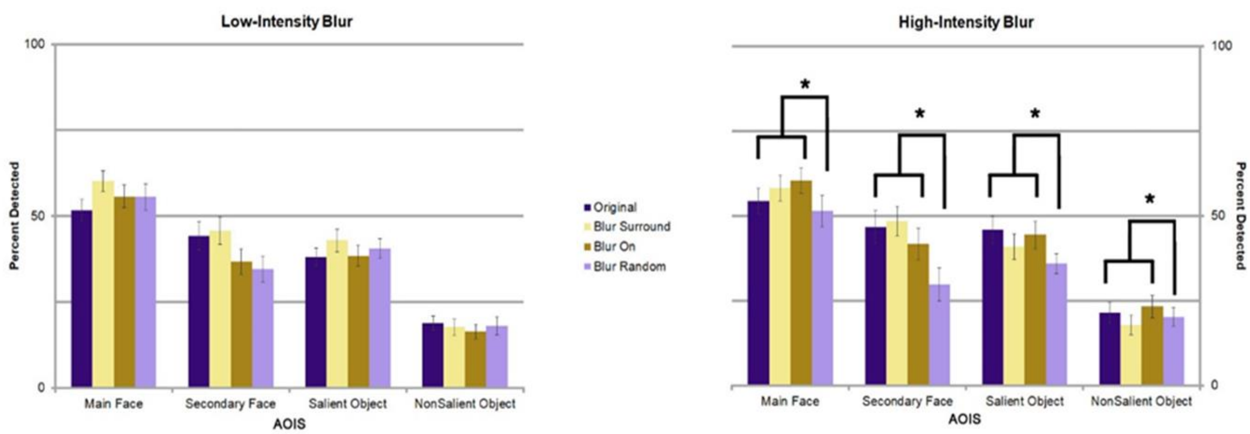

Figure 1.3: A. Percent detection of changes (accuracy) in Experiment 1B, averaged across participants for the low-intensity blur (left) and high-intensity blur (right) conditions. There is a main effect of AOI. Post-hoc tests with Bonferroni corrections revealed that observers detected color changes more accurately when the change occurred on the main face, secondary face, or salient object as compared to when the changes of the nonsalient object. A main effect of blur position was present only for the high-intensity blur conditions. Post-hoc tests with Bonferroni corrections showed that observers did worse when blur was placed in a random position as compared to when no blur was present or when blur was placed surrounding or on the area of interest ($p < 0.005$ as indicated by *).

Our original hypothesis was that blur as a highlight element would increase salience of the surrounded item. In contrast, we observed that blur seems to have a disruptive influence that distracts attention to feature changes. This was true specifically when blur was added inconsistent with artistic principles, positioned randomly in the art piece and of high intensity. We infer that artificially injecting strong texture elements is disruptive to the overall compositional balance in visual arts. That observers are sensitive to this modification is consistent with the importance of perceptual elements in navigating art pieces, particularly non-artistically trained individuals (Redies, 2015). This finding is also consistent with previous work demonstrating changes gaze exploration across classic and contemporary representational art pieces in which local features are artificially altered (Quian Quiroga & Pedreira, 2011).

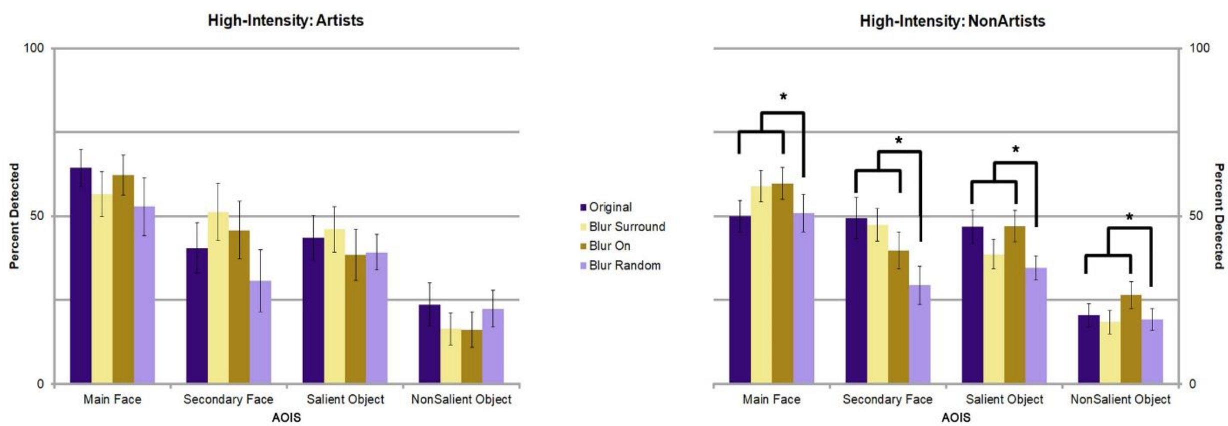

Figure 1.4: Change accuracy in Experiment 1B, computed separately for self-reported artists (left) and nonartists (right), for the high intensity blur condition (bottom). Both groups had change detection accuracies that varied with region of interest (main face, secondary face, or salient object more accuracy as compared to when the change was on the nonsalient object). Only participants without expertise were sensitive to the implementation of blur, with poorer change detection when blur included in random locations as shown by post-hoc tests with Bonferroni corrections ($p < 0.005$ indicated by *).

The effect of expertise:

A small proportion of our participants self-identified as visual artists or having experience critiquing art. We separately evaluated the effect of blur on the change blindness accuracies within these two groups (Figure 1.4). We found a main effect of blur implementation for the non-experts only ($F(3, 120) = 4.10$, $p<0.05$). Individuals that did not self-identify as having artistic training were less accurate in detecting changes when blur was inserted in a random location on the art piece. Self-reported individuals with artistic experience detected changes at equal rates across the levels of blur for the artists ($F(3, 51) = 1.28$, $p= 0.29$). However, the sample of artists is small (n = 18) and the results from the separate analyses are not sufficient evidence to conclude that there is a difference in performance between experts and nonexpert. Similarly, this does not discount the possibility of an effect of expertise if we were able to gather more art experts to participate in this experiment.

2.4 EXPERIMENT 1C: SALIENCE AND REGIONS OF CLARITY

In Experiment 1C we sought to evaluate whether regions of clarity in complex representational art, such as used in this study, benefit from attentional priority over blurred regions, as shown in previous studies of photographs and portraits (DiPaola et al., 2013; Enns & MacDonald, 2013; Smith & Tadmor, 2013). To test this, we include a condition in which blur is implemented consistent with near depth-of-field (i.e. blur imposed throughout the art piece, highlighting a single focal region). This experiment proceeded as in Experiment 1B, with the exception that we implemented the blur as large-scale, surrounding the targeted area of interest. In this strong test dominance of regions of clarity over regions of blur, we hypothesized observers' accuracy for detecting color changes would be optimized when the changed object retains detail and clarity.

Methods

Participants:

Experiment 1C included 74 individuals (57 females, 17 males), 12 of whom self-reported as artists. None of the individuals had previously participated in Experiments 1A or 1B. Individuals were recruited from the UCI Human Subject Pool and received course credit for their participation. All had normal or corrected to normal vision, were not colorblind, and gave verbal informed consent as approved by the University of California, Irvine IRB. One participant (non-artist) was dropped from the study post-hoc as a result of self-reported alcohol consumption prior to participating in the experiment.

Stimuli:

We implemented the same procedure as Experiment 1B, with the exception that the new Target Clarity condition (replacing the Blur Surround) was adapted to have blur applied to the entire art piece except for the figure or object attached to the targeted region. The blur was inserted using the Photoshop Gaussian filter tool, with a 2.5 pixel sigma full-width at half-magnitude (FWHM) bleed intensity, consistent with the low-intensity blur condition from Experiment 1B. The task otherwise proceeded as in Experiment 1B.

The experiment proceeded as a 4x4 factorial design that varied the implementation of blur with the area of interest, for a total of sixteen unique conditions. To prevent any impact of familiarity on change blindness accuracy, no individual saw the same image twice.

Results

Results from Experiment 1C are shown in Figure 1.5. A two-way ANOVA revealed a significant main effect of AOI ($F(2.71, 194.84) = 62.74$, $p<0.05$) such that viewers, again, were more accurate in detecting changes imposed on the main face, secondary face, or salient object compared to the non-salient object.

The ANOVA also revealed a significant main effect of blur implementation ($F(3, 216) = 7.92$, $p<0.05$). Individuals more accurately detected the changed targets when all other regions of the art piece were blurred except the target that contained the change to be detected (the target in the Target Clarity condition). We found no significant interaction between the AOI and

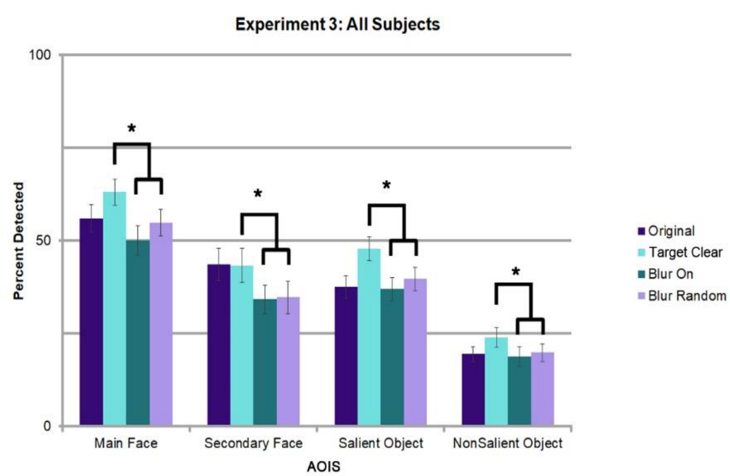

Figure 1.5: Percent change detection accuracy in Experiment 1C. Observers better detected changes when they occurred on the Main Face, Secondary Face, or Salient Object compared to when the change was on the NonSalient Object. Post-hoc tests with Bonferroni corrections revealed observers performed significantly better when the figure of AOI was cleared as compared to when blur was placed on or in a random position relative to the AOI ($p < 0.005$ as indicated by *).

where blur was placed ($F(7.62, 548.44) = 0.72$, $p= 0.67$). For all areas of interest, and by inference all levels of object salience, observers more accurately detected changes on items that appeared in their original form, clear and otherwise surrounded by blur.

Blur (and clarity) in visual arts implemented consistent with depth of field does indeed promote attention to the region of clarity. This finding is consistent with previous studies demonstrating attentional priority and enhanced attention to details within regions of clarity in art (DiPaola et al., 2013; Enns & MacDonald, 2013; Smith & Tadmor, 2013).

The effect of art expertise: When considered within our population of artists and non-experts (Figure 1.6), we found only non-experts had change detection accuracies that varied with blur implementation ($F(3, 180) = 7.255$, $p<0.05$). Change detection accuracy for the artists did not vary with blur implementation ($F(3,33) = 1.14$, $p=0.35$). As in Experiment 2, nonexperts are more susceptible to attentional biases imposed by manipulations of visual elements in art pieces which seems consistent with the principle that more art training induces a shift towards more cognitively controlled analysis of artistic works (Reber et al., 2004). Similar to Experiment 1B, our small sample of artists and separate analyses here are not sufficient evidence to say art experts and nonexperts are significantly different, but if we had a larger sample, we may find stronger evidence for an influence of expertise.

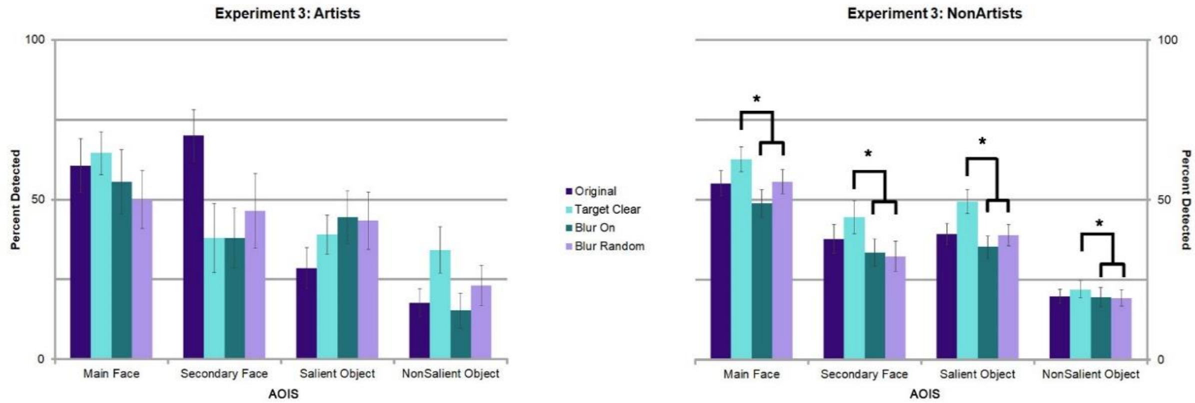

Figure 1.6: Change detection accuracy in Experiment 1C, computed separately for artists (left) and novices (right). We found no effect of blur implementation in the group of artists, whereas novices better detected changes when blur surrounded the ROI as compared with the other conditions (from post-hoc test with Bonferroni corrections as indicated by *).

2.5 EXPERIMENT 1: GENERAL DISCUSSION

The goal of this study was to evaluate the impact of blur as an artistic technique to control the relative salience of local elements within novel and complex, popular representational art. We hypothesized that blur consistent with artistic principles, namely surrounding an object of interest and implemented so as not to disrupt object boundaries and adjacent local features, would increase the local salience and elicit more detailed inspection by the observer. Our prediction was based on previous research finding increased gaze frequency and duration on regions of clarity in photography, portraiture and highly familiar representational art (DiPaola et al., 2013; Enns & MacDonald, 2013; Latif et al., 2014; Quian Quiroga & Pedreira, 2011; Smith & Tadmor, 2013). In our change detection paradigm, we anticipated increased perceptual salience would be apparent as improved detection for changes when imposed on objects surrounded by blur, drawing attention from blur used as a texture element.

Our results revealed internal consistency between measures of salience as assessed by explicit ratings (mouse clicks), implicit metrics (eye gaze) and change blindness accuracies. Items in the complex art pieces that were fixated more frequently were also more frequently rated as "important", and changes imposed on those items were more accurately detected. Selected elements do indeed stand out to viewers, even in complex art pieces, and these are identified with significant consistencies across individuals through a variety of methods.

Contrary to our hypothesis, we found that implementing blur in a way that is consistent with artistic technique did not boost the salience of the surrounding region. We did, however, find that including blur elements in random locations was disruptive to the visual exploration of the piece, seemingly by nonexperts. While our results are insufficient to conclude a difference between experts and nonexperts, it is still possible that an effect of expertise is present. Art expertise is an important factor in the visual analysis of art, associated with exploratory gaze patterns distinct from novices. Novices are less sensitive to the use of elements and techniques that contribute to the overall composition as evaluated by experts, and generally have a preference for reduced complexity in art (Antes & Kristjanson, 1991; Hekkert & van Wieringen, 1996; Koide et al., 2015; Nodine et al., 1993; Pihko et al., 2011; Silvia, 2006; Winston & Cupchik, 1992; Zangemeister & Privitera, 2013). Together these likely reflect an increased processing load in selecting and evaluating artistic elements by nonexperts, resulting in overall poorer "fluency" in evaluating art (Kozbelt et al., 2010; Perdreau & Cavanagh, 2013; Reber et al., 2004).

It is perhaps a bit surprising from our sample that artists were not influenced by the inclusion of blur to the extent of the novices. Indeed, art experts are generally more sensitive to alterations in local features that shift the compositional balance in art pieces (Locher et al., 1996). We note, however, that art expertise also bestows and ability to prioritize the structural elements that guide artists when composing an art piece, an indication of guided attention (top-down processes) driven by knowledge acquired through training (Koide et al., 2015; Kozbelt et al., 2010). This contrasts with novices, who require more information to judge pieces are appeared to be more driven by salient features in the piece (Kozbelt et al., 2010; Perdreau & Cavanagh, 2013). Coupled with the increased processing load imposed by parsing complex scenes, our experimental conditions may have combined to create conditions in which novices are particularly susceptible to salience-driven, bottom-up distraction.

Our findings contribute to the growing evidence that artistic techniques are tools that guide the experience of the viewer through attentive mechanisms, in addition to shaping the overall aesthetic experience. Local regions of salience in art pieces are effective in drawing attention, as shown by comparative analyses of eye gaze and physical salience as computed by contemporary models (Itti & Koch, 2001; Koide et al., 2015; Quian Quiroga & Pedreira, 2011). Blur as a means to draw attention to the surrounding item is not particular in highlighting local features, specifically in more experienced viewers that use knowledge-based strategies in optimizing their viewing experience.

An important consideration for change blindness experiments is the type of change that is inserted into the stimulus as a means for assessing salience. While in some studies using photographs, schematic objects are inserted or deleted (e.g. street sign, building window, traffic light; (Rensink et al., 1997; Simons & Rensink, 2005), we elected instead to change the color of an item, which allowed us to maintain the integrity of the art piece that may be otherwise detrimentally impacted by entirely constructing a new element within the piece. Our design is consistent with other change blindness studies that have capitalized on the effectiveness of color changes to assess the spatial allocation of attention (Rensink et al., 1997). We note, however, that the change detection paradigm itself has limited sensitivity to object salience, and that other approaches may yield subtle aspects of attention impacted by blur that we were unable to detect.

In conclusion, representational visual art is complex, with interactions between topic, context and implementation that are difficult to disentangle. Our study demonstrates the subtle benefits of blur in accentuating a region of interest when used in a way an artist would. In the populations where blur is ineffective, it is unclear whether it is just plain ignored or actively repels attention.

CHAPTER 3: EXPERIMENT 2

Eye Gaze Patterns & Models of Salience

3.1 INTRODUCTION

The way an artist composes an image can affect the viewers' attention and their overall perception of an art piece. As observed in Experiment 1, blur is an extrinsic property of an art piece that influences how attention is distributed across an art piece based on how and where the blur is placed on the image. To explore what other extrinsic properties capture a viewer's attention on an art piece, we can utilize eye-tracking as a measure of overt-attention (Blair et al., 2009; Hoffman & Subramaniam, 1995; Kowler, 1995; Parkhurst et al., 2002).

Different extrinsic properties such as perceptual features in the art piece can affect how overt attention is distributed over the art piece. For example, how elements are spatially organized can drastically change eye-gaze patterns such that changing the placement of one element can drive eye fixations to be placed differently as opposed to the original image (Quian Quiroga & Pedreira, 2011). Additionally, color influences the spread of eye fixations across an art piece; for example, art pieces in color have more spread out eye gaze patterns versus the grayscale version of the same art piece (Massaro et al., 2012).

In addition to the different perceptual features in an art piece, the content being represented in the art piece can direct our social attention. Studies have shown how overt attention is distributed across different types of art pieces. Representational art of scenery without figures has more widespread fixation patterns versus portraits where eye fixations congregate mostly on the face of the figure (Massaro et al., 2012). Other studies have further explored eye-gaze patterns on paintings with figures; the dynamics of how figures are portrayed affect how fixations are distributed. Art pieces depicting social interactions of figures had more fixations to the faces than art pieces depicting individual actions (Fischer et al., 2013; Villani et al., 2015). These studies show how social attention is reflexively captured by faces and implied motion of body figures even in art.

It is important to distinguish two different aspects of eye-tracking data: the spatial distribution of fixations and their sequence. The spatial distribution refers to; where the participant looked when viewing an art piece and, from this, we can try to infer what was particularly salient and/or interesting as they visually explored an image (Blair et al., 2009; Hoffman & Subramaniam, 1995; Oyekoya & Stentiford, 2006; Parkhurst et al., 2002). The sequence here refers to the order in which the eye fixations were made; this is often called the scanpath. It can tell us what people pay attention to first versus last (Drusch et al., 2014; Eraslan et al., 2016; Josephson & Holmes, 2002). Additionally, we can consider familiarity as another factor in the spatial distribution and sequence of eye fixations: is this the first time a person is viewing the image, or have they viewed it multiple times?

In visual exploration studies, both the spatial distribution and scanpath of fixations have been analyzed in order to look for patterns or strategies that people use when looking at a visual scene for the first time (Althoff & Cohen, 1999; De Lucio et al., 1996). Additionally, task instructions have been shown to affect the spatial distribution and scanpath of fixations on images compared to free viewing an image (Drusch et al., 2014; Tatler et al., 2010; Yarbus, 1967). Other visual exploration studies have analyzed eye fixations across multiple viewings of scenes. The results suggest that the scanpath from the first viewing of a stimulus is different from that later viewings of the same scene. However, once viewers become familiar with a scene the scanpath becomes less variable (Antes &

Kristjanson, 1991; Burmester & Mast, 2010; Muthumanickam et al., 2016; Pieters et al., 1999; C. M. Privitera et al., 2007; Claudio M. Privitera & Stark, 1998; C.M. Privitera & Stark, 2000).

The empirical aesthetics studies summarized previously mainly examined the spatial distribution of fixations for the first viewing of an art piece. These studies showed that people generally tended to look at the same regions on an art piece (Fischer et al., 2013; Massaro et al., 2012; Quian Quiroga & Pedreira, 2011; Villani et al., 2015). This observation has led to the suggestion that extrinsic properties of unfamiliar art pieces guide the observer's overt attention. Further support for this suggestion comes from studies in which large scale properties of an art piece, such as coloring, were altered between the first and second viewings (Massaro et al., 2012; Villani et al., 2015) and the spatial distributions of the fixations changed. For example, when subjects looked at the original colored art piece and the gray scale altered art piece, the overall spatial distribution of eye fixation clusters were different; however, across individuals, the spatial distribution of fixations were fairly similar within each version of an art piece (Massaro et al., 2012). Because, these clusters of fixations were similar between subjects within the colored versus altered version, it can be argued that the extrinsic property – color in this instance – has a large role in guiding overt attention during the visual exploration of the art piece.

Few empirical aesthetic studies have examined the scanpath of fixations made on art pieces and how these sequences compare between individuals (Pihko et al., 2011; C. M. Privitera et al., 2007; C.M. Privitera & Stark, 2000; Zangemeister & Privitera, 2013). Scanpath theory has primarily been applied to data based on multiple viewings of the same image by each observer. These data show that a person's scanpath remains consistent across multiple viewings of an image, but scanpaths across people often differ greatly for the same image (Noton & Stark, 1971; C. M. Privitera et al., 2007; C.M. Privitera & Stark, 2000; Stark & Choi, 1996). However, other reviews of scanpath theory and results from marketing studies, have found mixed results concerning the idiosyncratic nature of scanpaths on a visual scene. Some eye-tracking studies on webpages and ads showed that individuals tended to fixate on regions of interest in the same sequence with repetitive viewings supporting scanpath theory (Burmester & Mast, 2010; Josephson & Holmes, 2002; Pieters et al., 1999; Rosbergen et al., n.d.; Wedel & Pieters, 2000, 2008). However, other studies done on webpages have shown that individuals vary their scanpaths when they explore a webpage multiple times. These studies suggest that other intrinsic factors such as gender may affect scanpath patterns (Eraslan et al., 2016; Josephson & Holmes, 2002).

The differences in the heterogeneity of scanpaths described above may be due to the nature of the material being viewed: natural scenes, art pieces, ads, and webpages. Given this background, it is reasonable to ask if, when they look at unfamiliar art pieces, the scanpath across observers will be similar or more varied. If people do have similar scanpaths for unfamiliar art pieces, this would suggest that bottom-up processes triggered by extrinsic properties are governing the visual exploration more than top-down processes guided by intrinsic properties.

Eye fixation data has also been compared to the output of salience models and algorithms that predict regions of interests (ROIs). Salience models use different algorithms to predict local salience in visual scenes; for example, the Itti & Koch (2000) salience model, which has been widely used and studied, combines feature maps of low level perceptual features to produce a salience map. The Itti & Koch salience model was based on bottom-up visual processes in V1 (Itti, 2005; Katsuki & Constantinidis, 2014; Zhang et al., 2012). Studies examining the predictive power of salience models primarily compared the spatial distribution of eye fixations to salience maps of natural images (Amso et al., 2014; Bylinskii et al., 2018; Harel et al., 2007; Itti & Koch, 2000; Krasovskaya & MacInnes, 2019). Few studies have made comparisons of eye fixations and salience maps of art pieces. These studies have shown that salience maps do not capture every region a person fixates on in an art piece (Wallraven et al., 2009). Additionally, only a few previous studies have compared both the spatial distribution and the scanpath of individuals over different types of visual stimuli such as natural images and art pieces; these studies found that certain algorithms were better at capturing eye fixations for art pieces than for natural images (C. M. Privitera et al., 2007; C.M. Privitera & Stark, 2000).

Eyetracking data has many aspects that can be studied, and we will focus on the two aspects of spatial distribution and fixation sequence for the first viewing of art pieces to gain insight into what draws attention when looking at art pieces and what strategies people use to explore art pieces visually. We will look at both the spatial distributions and the scanpaths of the fixations and examine their similarity across people for the first viewing of a variety of art pieces. With these data, we can explore a variety of questions. Do individuals tend to look at the same regions on the art piece, and do they look at the same regions in a similar order in viewing an art piece for the first time? Additionally, we can ask how well the spatial distribution and scanpath data from human observers compare with the predictions derived from the salience maps produced by several models? If people tend to look at the same regions and salience models also predict those same regions, it would be evident that people are relying more on extrinsic properties to guide their overt attention as they explore the art piece for the first time. However, if people look at the same regions and salience models predict those regions poorly, then there is evidence that people may be using something other than what the salience models use to predict to guide their overt attention. We will also compare the scanpaths produced by human observers with those predicted from salience models. Privitera & Stark (2000, 2007) found little similarity between the scanpaths produced by human observers and those derived from algorithms; however, they also found low similarity across observers. These results were, however, based on data in which the observers viewed each image multiple times. It is possible that the first viewing of art pieces lead observers to produce scanpaths that are more similar to those derived from salience models if, on first viewing, people are relying more on the kinds of extrinsic properties, captured by the salience models, to guide their overt attention.

Based on these considerations, we will implement an eye-tracking experiment for subjects to free-view art pieces gathered from deviantart. These pieces are assumed to have low familiarity. We will analyze these art pieces using three salience models: Itti & Koch (2006), Graph-Based Visual Saliency - GBVS (Harel et al., 2007), and a Radial Symmetry (Loy & Zelinsky, 2003). The Itti & Koch (2006) model and the GBVS model have been widely studied using natural images, and we wish to see how the salience maps they produce compare with people's eye-tracking data for human-produced images. We also wish to use the Radial Symmetry model as it uses a symmetry transform to predict ROIs. This approach did well predicting ROIs that were similar to people's eye-tracking data on art images in Privetera & Stark's (2000, 2002) experiment. We hypothesize that the spatial distribution and scanpaths between subjects and between subject and models will be highly similar for the first viewing of an art piece where subjects will rely more on extrinsic properties to guide their attention across an art piece for the first time.

3.2 METHODS

Participants:

The subject data used in Experiment 2 is the same subject data from the eye-tracking task in Experiment 1A. Sixteen individuals (6 male, 10 female) participated in the eye tracking task. All participants had not participated in any of the previous mentioned experiments. All had normal or corrected to normal vision, were not colorblind (as indicated by self-report) and gave verbal informed consent approved by the University of California, Irvine IRB. All participants received course credit for their participation.

Stimuli:

The original 68 art pieces that were gathered from deviantart artists in Experiment 1 were utilized in Experiment 2.

Procedure:

The procedure in which the eyetracking data was collected is the procedure in Experiment 1A. All participants viewed each of the 68 art pieces for a minimum of 5 seconds, with no direct instructions or characterizations required (free viewing). Observers were instructed to press the spacebar when they were finished inspecting the images. Viewing order of the images was randomized.

Salience Model implementation:

The Itti and Koch (2006) salience model extracts low level visual features – color, orientation, and contrast – from an image to create separate feature maps. These feature maps are then normalized and a winner-take-all algorithm is applied to produce a salience map. Salience maps were created for each art piece using the Itti & Koch Salience toolbox provided in the GBVS toolbox in Matlab (Harel, 2008).

The Graph-Based Visual Saliency (GBVS) model extracts similar low-level visual features as the Itti & Koch salience model – color, orientation, and contrast. The GBVS extracts these features in separate feature maps that are then normalized into activation maps by using a Markov chain. The GBVS maps were created for each art piece using the GBVS toolbox in Matlab (Harel, 2008).

The Radial Symmetry Transform model (Loy & Zelinsky, 2003) produces a salience map of points with radial symmetry based on contrast. This model takes in a radius parameter for how many pixels to define a region for symmetry and a sigma parameter for the gaussian kernel that is applied at each region extracted. We applied the same default radial strictness parameter defined in the paper into the Matlab function. The radial symmetry maps of light and dark areas combined were created for each art piece using the Radial Symmetry functions in Matlab (Sandro, 2020).

First-Level Clustering:

A first level clustering procedure was used similar to Privitera and Stark (2000, 2007) on the fixation data and salience model predictions to account for microsaccades in the fixation data and to condense the number of ROIs from the salience model to a reduced number. The resulting data from the first level clustering will be used to calculate similarity of position (S_p) and similarity of scanpath (S_s) between subjects and between subject and models. For the eye-tracking data, fixations that were made close in distance to one another consecutively were clustered together into one fixation to remove any microsaccades. For each subject's eye-tracking data, we examined the first fixation which was in the center of the image for each trial from the calibration that was done for each trial; if it deviated more than 10 pixels, then we adjusted the position of subsequent fixates according to the deviance. We only found a few trials to have deviated more than 10 pixels with a maximum deviance of 26 pixels from the center of the art piece. The first fixation was removed from the sequence of eye fixations because it was from the calibration sequence at the beginning of each trial. An average of 15 fixations were left for each subject and art piece.

For the salience maps, the local maxima were extracted, and a distance clustering algorithm was applied step by step in order to produce approximately 15 ROIs for each salience map. On each step of clustering the local maxima, the local maximum with the highest intensity value from the salience map would become the locus of that cluster, and any other local maxima within the clustering distance defined would be clustered together. The clustering distance would increase by 10 pixels for the next step until approximately 15 ROIs were left to correspond to the average number of eye fixations made on each art piece.

Figure 2.1 First-level clustering.
The raw eye-fixations and scanpath of a subject are shown on the left with the first calibration fixation marked with an "X" in the center on the art piece. Eye-fixations that were made consecutively near one another were considered micro-saccades and clustered together. A couple clusters of closely made eye fixations are highlighted by the yellow circles. The right image shows the resulting eye-fixations and scanpath after this first-level clustering procedure.

3.3 RESULTS & DISCUSSION

A second level clustering procedure similar to Privitera and Stark (2000, 2007) was applied to pairings of data. Depending on the pairing being analyzed, the ROI's derived for each subject were combined with those of either every other subject or with those derived from one of the salience models. In each pairing, a clustering algorithm, implemented in Matlab, was used to group the ROIs from the two sources (Marcon, 2019). ROIs were clustered together if they were separated by a distance of 90 pixels or less; this is about 2 degrees of visual angle or somewhat less than the visual region viewed by the fovea (Hirsch & Curcio, 1989). After the second level clustering, each ROI, from either source, was labelled to reflect the cluster it was in (Figure 2.2). The resulting clusters, which could be made up of ROIs derived from either or both of the sources being paired, were then used to calculate the spatial similarity score and the sequence similarity score (Figure 2.2).

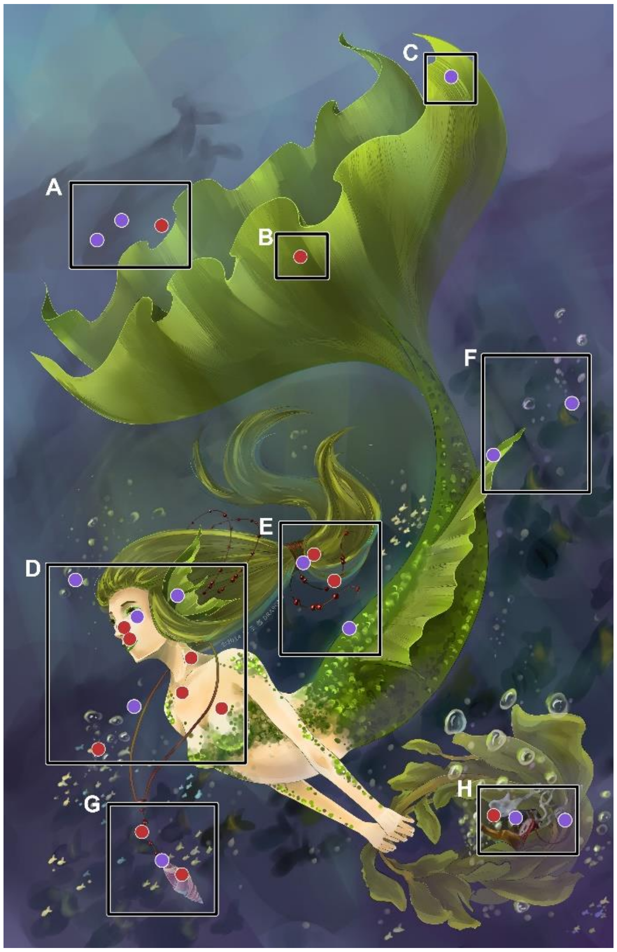

Figure 2.2 Second-level clustering.
Two subjects' eye-fixations are shown above (subject 1 in red and subject 2 in purple) after a second-level clustering procedure was applied. These clusters will be used to calculate the Jaccard similarity index for the S_p score for this pairing. An arbitrary letter was applied to each cluster in order to use these clusters to calculate the S_s score for the similarities of this pair's scanpaths.

Similarity of Position (S_p)

The Jaccard similarity score was calculated in Matlab by taking the ratio of number of clusters for a pairing that included ROIs from both sources and dividing this by the total number of clusters for that pairing present in the art piece. For example, in Figure 2.2, four of the clusters derived from the pairing had ROIs from both sources, and there was a total of 6 clusters resulting in $S_p = 0.67 = 4/6$. The closer S_p is to 1, the more the ROIs from both clusters are spatially similar – 1 indicating that ROIs from both sources were present in all of the clusters.

S_p (Jaccard) Similarity t-test Table

	Mean	SD	Itti & Koch vs. Subject	GBVS vs. Subject	Symmetry vs. Subject
Subject vs. Subject	0.49	0.08	$t = 5.35$ $p = 1.1e-6$	$t = 3.34$ $p = 0.001$	$t = 15.29$ $p = 1.6e-23$
Itti & Koch vs. Subject	0.41	0.10	--	$t = -2.84$ $p = 0.01$	$t = 11.34$ $p = 3.1e-17$
GBVS vs. Subject	0.45	0.09	--	--	$t = 11.88$ $p = 3.9e-18$
Symmetry vs. Subject	0.30	0.07	--	--	--

Table 2.3 S_p (Jaccard) Similarity t-test Table.
A paired t-test was conducted on the Jaccard similarity scores (S_p) for each comparison between source pairings for each art piece. The upper-triangle for the t-test between pairings is shown.

S_p was highest when a subject's ROIs were paired with those of other subjects; all of the pairings of subject ROIs with those derived from the salience models were significantly lower (Table 2.3). Interestingly, this average S_p score for between-subject comparisons is similar to that reported in Privitera and Stark's (2000) study (S_p = 0.54). Although the ROIs of a subject are best predicted by those of another subject, the overlap is far from perfect, with only roughly half of the ROIs produced by a subject being similar to those produced by another subject.

Comparing the ability of the various salience models to predict subject ROIs, the Itti & Koch (2006) salience model and the GBVS model did significantly better than the Radial Symmetry model (Table 2.3). From this we might infer that both the Itti & Koch salience model and the GBVS model capture more of the extrinsic properties that guide human fixations during the first exploration of an art piece than the other two models. This corroborates with the fact that these models extract similar low-level visual features; however, these models remain significantly different from one another in performance and this could be due to how these models use different procedures for combining feature maps to calculate relative salience in an image. One possible explanation for why S_p of subjects with other subjects is higher than that of subjects with the GBVS and the Itti & Koch salience model may be that these model don't recognize faces well as humans and thus fail to give faces sufficient salience (Borji et al., 2013; Cerf et al., 2009).

We analyzed the proportion of ROIs made on faces for subjects, the Itti & Koch salience model, and the GBVS model. Figure 2.4 shows the proportion of fixations or ROIs identified on a face compared to the number of faces present on the art piece. Art pieces that didn't have a face present were excluded from this analysis. Subjects (*median* = 0.84) overall fixated a higher proportion of the available faces than either the Itti & Koch (*median* = 0.50) salience model or the GBVS model (*median* = 0.67). A Wilcoxon Signed-Ranks test showed strong evidence that the Itti & Koch model did not identify faces as well compared to humans (z =3.3 , p = 9.8e-4). There is weaker evidence that humans did significantly better than the GBVS model in identifying faces (z = 2.3, p = 0.02). The Itti & Koch model did not differ significantly from the GBVS model (z = -1.5, p = 0.1), so we cannot conclude that the GBVS model performs better in identifying faces in art pieces. These results suggest that faces are an extrinsic property that largely captures human attention, and

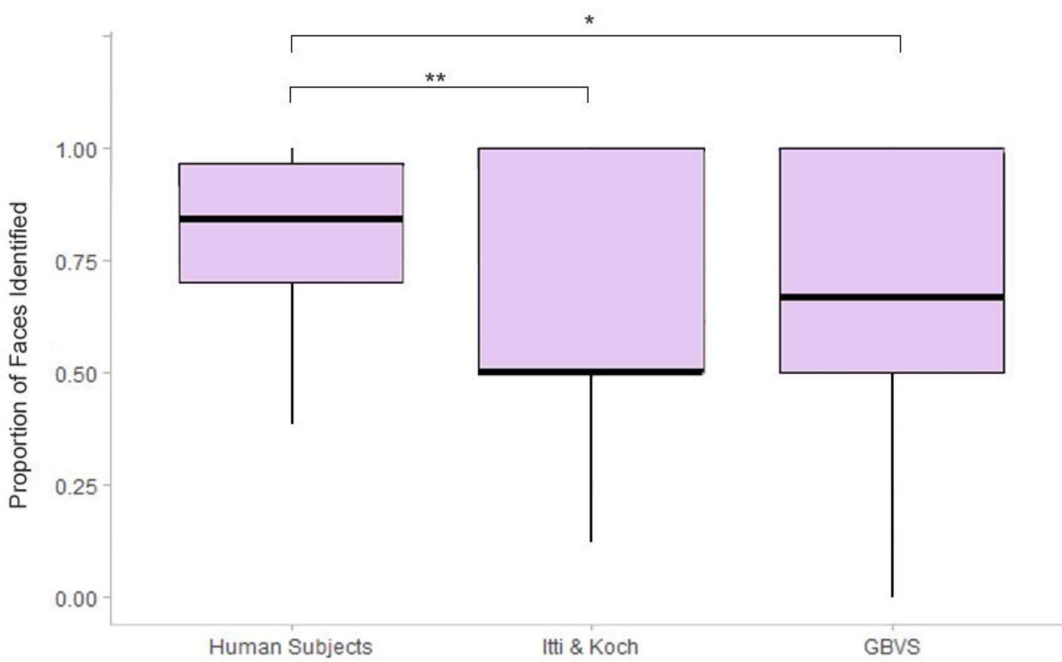

Figure 2.4 *Boxplot of Proportion of Face Identified.*
Each box represents the source of ROIs identified on an available face in an art piece. For example, if an art piece had two available faces, and a source identified an ROI at least once on both faces, the proportion would be 2/2. The bold black lines denote the median. Human subjects were significantly different from the Itti & Koch salience model (**p = 9.8e-4 from a Wilcoxon Signed-Ranks test). Human subjects were also different from the GBVS model (*p = 0.02 from a Wilcoxon Signed-Ranks test). There was no significant difference between the Itti & Koch model and the GBVS model in the proportion of faces these models identified.

these salience models do not include feature detection that captures faces into their salience maps.

Our results corroborate with our hypothesis that the GBVS model would do better than the Itti & Koch salience model in predicting subject ROIs. The GBVS model relies on a different algorithm in combining activation maps by computing the equilibrium distribution from a Markov chain while the Itti & Koch model rely on a winner-take-all approach from combining feature maps together. In previous studies, the GBVS model predicted human fixations on natural images better than the Itti & Koch model. It is evident in this experiment that this is true for art pieces as well. However, there was still a significant difference for between-subject comparisons and the subject versus GBVS comparisons meaning that the GBVS did not capture all of the ROIs that humans fixate on. Art pieces are different from natural images and photographs in the sense that art pieces are created by another human being with their own goals on what they wish to portray. We can also argue that art pieces may also have more details and exaggerated features than what a photograph of a natural scene might have (e.g. a photo of a forest background with two deer in the foreground), and thus the GBVS model doesn't capture all of the ROIs that humans look at.

Additionally, the radial symmetry model here did poorly compared to the symmetry algorithm that Privitera & Stark utilized in their study in the context of paintings (2000). It is possible that the symmetry model may only work on specific sets of art pieces where symmetry is core to the composition of the art piece such as portrait style paintings focused on the bust upward; this is not true of the art pieces we gathered off deviantart where the art pieces included full body and dynamic poses. Privetera & Stark specifically observed repeated viewings of the paintings rather than the first viewing. For the first viewing of an art piece, asymmetrical points may be more salient than symmetrical points in an image which would mean that people will look at the asymmetrical points first.

Sequence Similarity (S_s)

The sequence similarity score was calculated in Matlab by taking 1 minus the calculated costs of string editing between the strings created for both sources divided by the longest string length of the pair (C. M. Privitera et al., 2007; C.M. Privitera & Stark, 2000). A string of letters would be produced from each source by assigning each cluster a letter; then each ROI from a source would be assigned the letter based on which cluster they were in (Figure 2.2). For example, subject 1 (red) in Figure 2.2 has a string of *ddeadehdgdgdb* and subject 2 has a string of *dedaghedacfhfd*. The strings would also be compressed where if there was a sequence of the same letter being repeated consecutively, only one iteration of that letter would remain in that position (Choi, et al., 1995). The total cost from string editing for this pair would be 9 which would result in $S_s = 1 - (9/14) = 0.36$. The closer S_s is to 1, the more similar the scanpaths of the pairing where the strings are the same and no edits (costs) are needed.

Overall, S_s was the highest when a subject's ROIs were compared to another subject while S_s for pairing of subject ROIs with salience model ROIs were significantly lower (Table 2.5). The S_s score reported here for between subject ROI comparisons is higher than what had been reported in both Privitera and Stark's (2000) and Zangemeister & Privitera's (2013) studies for paintings. These previous studies reported S_s scores being approximately 40% lower than their reported S_p scores. In our experiment, we assume that subjects are most likely viewing the art pieces for the first time due to these painting belonging to niche artists. Our higher S_S scores provide evidence that subjects are looking at similar ROIs in a similar order in which subjects are relying more on extrinsic properties to guide their attention as they visually explore an art piece for the first time. Our findings of lower Ss scores between subjects and salience models is similar to the low S_S scores between subject and algorithm comparisons in Privitera and Stark's study (2000). These salience models do not capture the order in which subject look at these ROIs. Even though the Itti & Koch model did a better job at predicting subject ROIs than the other salience models, this model performed similarly to the other models in terms of predicting subject scanpaths. We can conclude that these salience models weigh the relative salience of ROIs differently than humans.

S_S Similarity t-test Table

	Mean	SD	Itti& Koch vs. Subject	GBVS vs. Subject	Symmetry vs. Subject
Subject vs. Subject	0.40	0.06	t = 28.82 p = 1.8e-39	t = 21.48 p = 9.4e-32	t = 22.334 p = 9.4e-33
Itti & Koch vs. Subjet	0.19	0.04	--	t = -7.18 p = 7.2e-10	t = -4.20 p = 8.0e-5
GBVS vs. Subject	0.23	0.04	--	--	t = 1.24 p = 0.22
Symmetry vs. Subject	0.22	0.05	--	--	--

Table 2.5 S_S Similarity t-test Table.
A paired t-test was conducted on the sequence similarity score (S_S) for each comparison between source pairings for each art piece. The upper-triangle for the t-test between pairings is shown.

Conclusion

Humans tend to look at similar ROIs in an art piece in a similar order when they view an art piece for the first time based on the between subjects S_p and S_s scores we've reported. This highlights evidence that we rely more on extrinsic properties of an art piece to guide our overt attention for a new viewing. We also seem to weigh the relative salience of these extrinsic properties similarly as well in which salience models have not yet been able to replicate. Previous studies have shown that people's scanpaths differ between individuals when they've repeatedly viewed an image, and the scanpaths within a single individual in repeated viewings is highly similar (Eraslan et al., 2016; Josephson & Holmes, 2002; C. M. Privitera et al., 2007; C.M. Privitera & Stark, 2000). This evidence indicates their scanpaths may be modulated more by intrinsic properties of the person in which they have their own goals or things they are interested in exploring after they have become familiar with the art piece. Our experiment is limited to subjects viewing the art piece for the first time without repeated viewing late, so we cannot fully conclude that the first viewing is completely different from repeated viewings later on for our set of art pieces. This is something we can expand upon in the future for this study.

CHAPTER: EXPERIMENT 3

AQ Traits and Evaluations of Preference and Visual Complexity

4.1 INTRODUCTION

Many studies have explored the concept of visual complexity, how to quantify it using different mathematical models, and how visual complexity relates to different outcomes of the aesthetic experience (Beauvois, 2007; Daniel E. Berlyne, 1970; Bies et al., 2016; Corchs et al., 2016; A. Forsythe et al., 2011; Nadal et al., 2010). Many of these studies focus on the visual complexity of websites to improve user interface navigation or on the appeal of ads (Deng & Poole, 2010; Michailidou et al., 2008; Reinecke et al., 2013; Tuch et al., 2009). Studies measuring the visual complexity of website designs looked at measurable extrinsic properties such as entropy, colorfulness, or png/gif compression ratio and compare these measurements to participant's ratings of visual complexity (A. Forsythe et al., 2011; Machado et al., 2015; Manuela M. Marin & Leder, 2013; Pieters et al., 2010). However, these studies have shown mixed results where some studies showed a correlation between these extrinsic properties and participants' rating of visual complexity and other studies showed no correlation (Miniukovich & De Angeli, 2014; Nadal et al., 2010; Pieters et al., 2010). Additionally, these studies illustrate a difficulty of comparing empirical aesthetic studies because they measure different types of participant rating as dependent variables. For example, many of these studies attempt to observe the relationship between visual complexity and "aesthetic" beauty ratings (A. Forsythe et al., 2011; Alex Forsythe et al., 2017; Friedenberg & Liby, 2016; Street et al., 2016) while some studies observed the relationship between visual complexity and "aesthetic" preference ratings (Osborne & Farley, 1970; Reinecke et al., 2013; Tuch et al., 2012). These studies have not led to a clear consensus on the relationship between mathematical measures of visual complexity, perceived complexity ratings, and aesthetic experience outcomes: some studies have argued that these measures were predictive of participant ratings and other studies argue that these measures were not predictive at all (Corchs et al., 2016; A. Forsythe et al., 2011; Reinecke et al., 2013; Street et al., 2016).

A second line of research has looked at the role of intrinsic properties in perceived complexity and aesthetic experience outcomes of a stimulus. Specifically, these studies try to explain why perceived complexity ratings and aesthetic experience outcome ratings are not always correlated by looking at intrinsic properties of the observers. We know from previous studies that intrinsic properties such as art expertise can influence aesthetic experience outcomes such as preference (Furnham & Walker, 2001; Illes, 2008; Uusitalo et al., 2009), and so it is reasonable to consider how intrinsic properties might affect perceived complexity ratings as well. One study considered gender and age as intrinsic properties that might be influential in the aesthetic experience; however, neither gender or age was found to mediate the relationship between perceived complexity and ratings of beauty (Reinecke et al., 2013). Other studies have looked at other intrinsic properties such as expertise and personality traits. Studies have found that the correlation between perceived complexity ratings and preference ratings did not depend on these intrinsic factors (Osborne & Farley, 1970; Street et al., 2016). However, others have shown that the correlation does depend on expertise (Alex Forsythe et al., 2017; Mayer, 2018).

We see from these studies that the relationship between perceived complexity and preference is still unclear. To add another level to this relationship, we also do not have clear answers on how different intrinsic properties affect these two ratings. However, there are two theories that can guide us to understand this complex relationship better: the hedonics model (set point theory), and fluency theory. The hedonics model encompasses the set point theory where people have a sweet spot for preference on a given dimension for a stimulus (Berlyne, 1972). For example, if we were to consider complexity as the dimension of interest, one person might have a set point for high complexity stimuli, and so they would prefer high complexity stimuli, have a lower preference for moderately complex stimuli, and the least preference for low complexity stimuli (Figure 3.1a). For this observer, complexity would be positively correlated with preference. However, the set point can differ between individuals, and this, along with differences in subject populations, may explain the failure to find a consistent correlation between perceived complexity ratings and preference ratings in previous studies. To see this, consider a hypothetical observer with the complexity set point near the middle of the complexity range. For this observer, moderately complex stimuli will elicit the highest preference and preference will fall off for both more complex and less complex stimuli – an inverted-U relationship that will lead to a correlation between complexity and preference that is close to zero (Figure 3.1b). Finally, at the other extreme is an observer with a set point at the low end of the complexity range. For such an observer, there will be a negative correlation between complexity and preference (Figure 3.1c). These set point differences may be tied to intrinsic properties that influence the fluency with which observer process stimuli. For example, fluency theory postulates that the easier something is to process, the more likable or preferred it is (Reber et al., 2004). This suggests that experience or expertise might be an important factor. In addition, however, set points might simply be tied to personal preference.

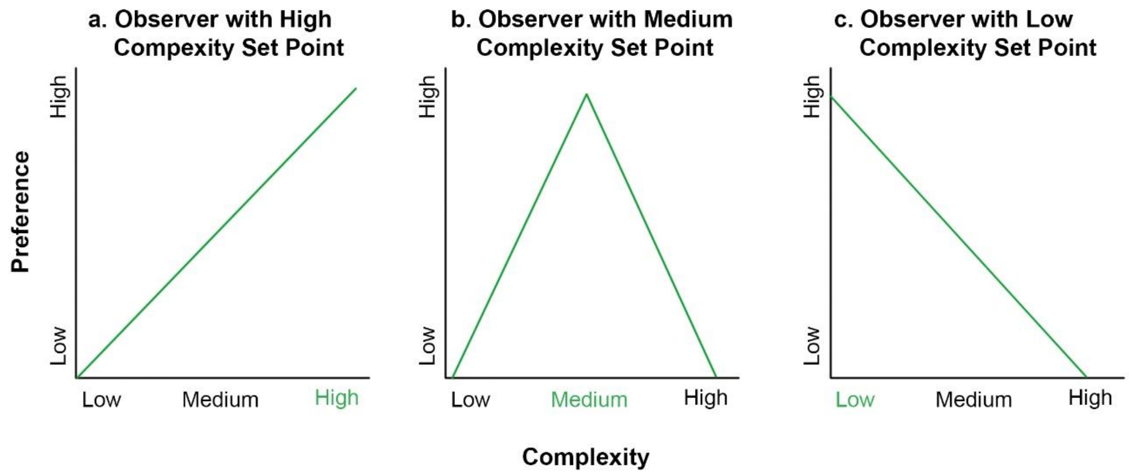

Figure 3.1 Set Point Trends.

An observer with a preference for high complexity items is shown with a positive correlation in 3.1a An observer with a preference for medium levels of complexity is shown with the inverted-U trend in 3.1b. Lastly, an observer with a preference for low complexity items is shown with a negative correlation on in 3.1c.

We specify perceived complexity and preference as our two measures of interest; the question of what intrinsic property should we consider still remains. The intrinsic property we will consider is the Autism Quotient (AQ) which hasn't been studied yet in the context of the aesthetic experience, and this trait may alter perceived visual complexity and preference as it is associated with characteristics such as attention to details (Baron-Cohen et al., 2001). The AQ was developed to measure traits such as attention to detail associated with individuals on the Autism Spectrum that can be measured in the non-clinical population; it is not a diagnostic tool (Baron-Cohen et al., 2001; Hoekstra et al., 2008; Hurst et al., 2007). Previous research on Autism and art primarily observed these individuals in the context of savant case studies and art therapy (Durrani, 2014; Emery, 2004; Martin, 2009; Pring et al., 1995, 2010, 2012; Schweizer et al., 2014). However, other studies on

Autism and visual perception have shown interesting results such as that individuals on the spectrum are less susceptible to visual illusions (Chouinard et al., 2016). This result may be due to traits in Autism patients such as attention to detail that is captured by the AQ. Based on fluency theory, it is possible that these traits may influence where the set point for complexity lies for these individuals based on how they attend to details of a stimulus.

The type of art piece may contribute to how people rate perceived complexity and preference. Some empirical aesthetic studies only focus on one type of art such as abstract art as a way to control for variability of art in general (Braun & Doerschner, 2019; Feist & Brady, 2004; Koide et al., 2015; van Paasschen et al., 2015). Including art pieces of several types in this study, provides us both with the possibility of extending the generality of its results or of detecting important differences in the complexity-preference relationship across types of art. We may observe that people will rate different types of art pieces differently on perceived complexity and preference. For example, we may find that observers rate representational art pieces to be less complex and more preferable while they rate abstract art pieces to be more complex and less preferable. This observation would be consistent with the set point theory which is also included in the Hedonic Model of aesthetics. Additionally, intrinsic properties such as the AQ may also interact with extrinsic properties in the rating of these art pieces so that High AQ individuals might rate representational paintings to be less complex and preferable while Low AQ individuals might rate representational painting to be more complex and preferable.

Experiment 3 will have participants complete two tasks administered approximately a week apart. For both tasks, a participant simultaneously viewed a pair of art pieces and, depending on the task, indicated which was more complex or preferred.

This forced choice task is different from previous empirical aesthetic experiments where they had participants use a slider or Likert scale to indicate ratings. Sliders and Likert scales have been shown to be less valid in capturing ratings because individuals don't always use the entire scale (Dittrich et al., 2007; Joshi et al., 2015). This experiment will use a forced choice methodology to create a rank ordering of the art pieces. The art pieces were selected from three categories: Representational without Face, Representational with Face, and Abstract art pieces. For simplicity we will refer to these 3 categories as "Representational," "Face," and "Abstract." The paired comparisons included all pairwise combinations of art pieces, both within and across the three categories. Based on the paired comparison data, a ranking of the art pieces for a participant, according to either preference or complexity, was generated using the EloChoice package (Clark et al., 2018).

We hypothesize that, compared with lower AQ participants, the rankings for the higher AQ participants will place pieces that are either representational or abstract at the higher end of the complexity scale and these art pieces will be more preferrable. This outcome is probable because high AQ individuals are likely to have higher attention to detail which may make it easier for them to process these art pieces that are perceived to be complex and be more preferred. Additionally, we hypothesize that Faces will be less preferred amongst High AQ individuals because social attention studies have also shown that Autism patients tend to avoid attending to faces and attend more often to nonsocial stimuli (Kikuchi et al., 2009; Riby & Hancock, 2008; Sasson & Touchstone, 2014; Tyndall et al., 2018).

As mentioned in the beginning, studies have focused on comparing algorithm measurements and perceived complexity, but they had mixed results. We will include two measures that have been shown in some studies to be correlated with perceived complexity ratings: entropy and a colorfulness measure(Hasler & Suesstrunk, 2003; Reinecke et al., 2013). They are included to see if these measures correlate with ratings of perceived complexity with our set of art pieces. However, we hypothesize that we may not find a strong correlation for either complexity measure. Our primary focus for this experiment is on the relationship between how a person rates perceived complexity and preference on an art piece.

4.2 METHODS

Participants:

Forty-eight individuals (9 males, 36 females, 3 preferred not the state) participated in Experiment 3. Four individuals were excluded for failing to show for the second day of the experiment and thus had incomplete data. All had normal or corrected to normal vision, were not colorblind (as indicated by self-report) and gave verbal informed consent approved by the University of California, Irvine IRB. All participants received course credit for their participation.

Stimuli:

Thirty art pieces were collected from the ARTstor database from various museums for academic use under a noncommercial creative common license. These art pieces were organized into 3 categories by 4 industry artists with ranging experience from 3-6 years: Representational without Faces, Representational with Faces, and Abstract (without recognizable objects). We will refer to these categories as Representational, Face, and Abstract art categories respectfully to be more concise. These art pieces were chosen to have a ratio sized of 4:6 (length and width) so that they could be displayed in pairs without being too small (or have large size discrepancies based on height of length). These art pieces were resized with respective ratios to be display at 15 degrees visual angle in pairs with one another side by side (left and right) in random order.

The Autism Quotient (AQ) inventory is a 50-item questionnaire that reliably measures factors considered to be major traits of autism that we can assess in non-clinical samples such as attention to detail, attention switching, imagination, communication, and social skills. This measure of AQ has been tested for reliability and validity in nonclinical samples (Hoekstra et al., 2008; Hurst et al., 2007; Stewart & Austin, 2009; Voracek & Dressler, 2006; Wakabayashi et al., 2006). This is not a diagnostic measure for ASD, it is a measure for traits heavily associated with autism in which individuals on the Autism Spectrum are very likely to score high on this inventory.

The Art Expertise Questionnaire is a 10-item survey that measures art expertise on the basis of art classes (both practical and theoretical), how long they've been doing art, time spent in museums, and art history (Chatterjee et al., 2010). This questionnaire has been used to measure art expertise in the sense of art knowledge and theories rather than in skills and implementation of those skills (Pelowski et al., 2017; Silvia, 2013; van Paasschen et al., 2015). Individuals were also asked to self-identify as visual artists as well where many artists nowadays are not required to have a degree necessarily in the arts but rather experience and demonstrate art skills relevant to industry needs.

Procedure:

Participants completed a two-day study with 6 to 10 days in between sessions to alleviate problems with becoming familiarized with seeing the art pieces multiple times. On Day 1 participant complete one of the following surveys: The Art expertise Questionnaire or the Autism Quotient. They also competed one of two tasks: Preference ranking task or Visual Complexity ranking task. On Day 2 they complete the remaining survey and task they did not do on Day 1. The order of surveys and tasks were randomized for each participant.

In the Preference Task, participants were shown pairs of the art pieces and they were asked to choose which art piece of the two they preferred more by pushing the corresponding left or right button. Participant saw each pairing of the 30 art pieces once and in a randomized order for a total of 435 trials. Art pieces were resized with preserved size ratio to subtend approximately 15 degrees visual angle and were shown side by side (left and right) where participants could choose which one they preferred more by pressing the corresponding left or right button. In the Complexity task, the procedure and display of art pieces remained the same as the Preference Task; however, participants were asked to choose the art piece they felt was more complex out the pairing by pushing the corresponding button.

AQ and Art expertise scores were calculated based on responses given on the surveys according to the score sheet from their respective inventories (Baron-Cohen et al., 2001). High AQ scores were above the average score of 19 previously reported in Baron-Cohen's evaluation. High AQ participants had a range from 23 to 45. Low AQ scores for participants ranged from 7 to 16. For art expertise, only two subjects scored above 23 points along with self-identifying themselves as artists. Due to a small sample size of art expertise, we did not further analyze subject ratings in the context of art expertise.

Visual complexity algorithm measures:

We calculated objective visual complexity for each art piece using an entropy algorithm and a colorfulness algorithm that had been previously used in visual complexity studies (Hasler & Suesstrunk, 2003; Madan et al., 2018; Reinecke et al., 2013). This was used as a method to quantify visual complexity as an extrinsic property to see whether these measures correlated with how participants ranked our art pieces on perceived visual complexity. However, based on previous research, we do not expect a correlation of these measures to perceived complexity.

mElo Analysis:

An mElo score was calculated for each art piece and participant using the EloChoice package(Neumann, 2019). The Elo rating system was originally used to rank players for games such as chess based on information from previous matches between players that can be used to predict future outcomes and whether that prediction matches the outcome (Albers & de Vries, 2001; Clark et al., 2018; Neumann et al., 2011). This ranking system can also be applied to paired comparisons data for visual stimuli such as art pieces by participants (Clark et al., 2018). For each trial, the participant selects a "winner"; the art piece that is preferred or more complex. Based on this outcome the algorithm reduces the score of the losing piece and raises that of the winning piece by the same amount. After all the paired comparisons have been considered, the points for each art piece can be used to rank them. Because, initially, all the of art pieces are given zero points and the winner of a trial is always being given points from the loser, the sum of the points across all the art pieces is always zero. To reduce the influence of sequence effects, the process is repeated an additional 999 times with the order in which the trial data are entered randomized between runs. The mElo score for each art piece is the average of its Elo scores across these 1000 runs.

4.3 RESULTS & DISCUSSION

A Pearson's r correlation coefficient was calculated for entropy and colorfulness scores of the art pieces and each person's perceived complexity mElo scores. Figure 3.2 shows the distribution of the resulting correlation coefficients broken out for the low and high AQ groups. A one-sample t-test showed that the distribution of correlation coefficients for the entropy algorithm in both high ($t(18) = 1.2215$, $p = 0.24$) and low ($t(24) = 0.97$, $p = 0.34$) AQ groups was not significantly different from a distribution with a mean of zero. Similarly, the distribution of the correlation coefficients for the colorfulness algorithm was also not significant for the high AQ group ($t(18) = -1.84$, $p = 0.08$). We did find the colorfulness correlation coefficients to be significant in the low AQ group ($t(24) = -3.35$, $p = 0.003$). However, this correlation is negative and does not correspond to the positive correlations found in previous studies. There is no sensible explanation for this negative correlation between colorfulness and perceived complexity; thus, it will be treated as a zero correlation here.

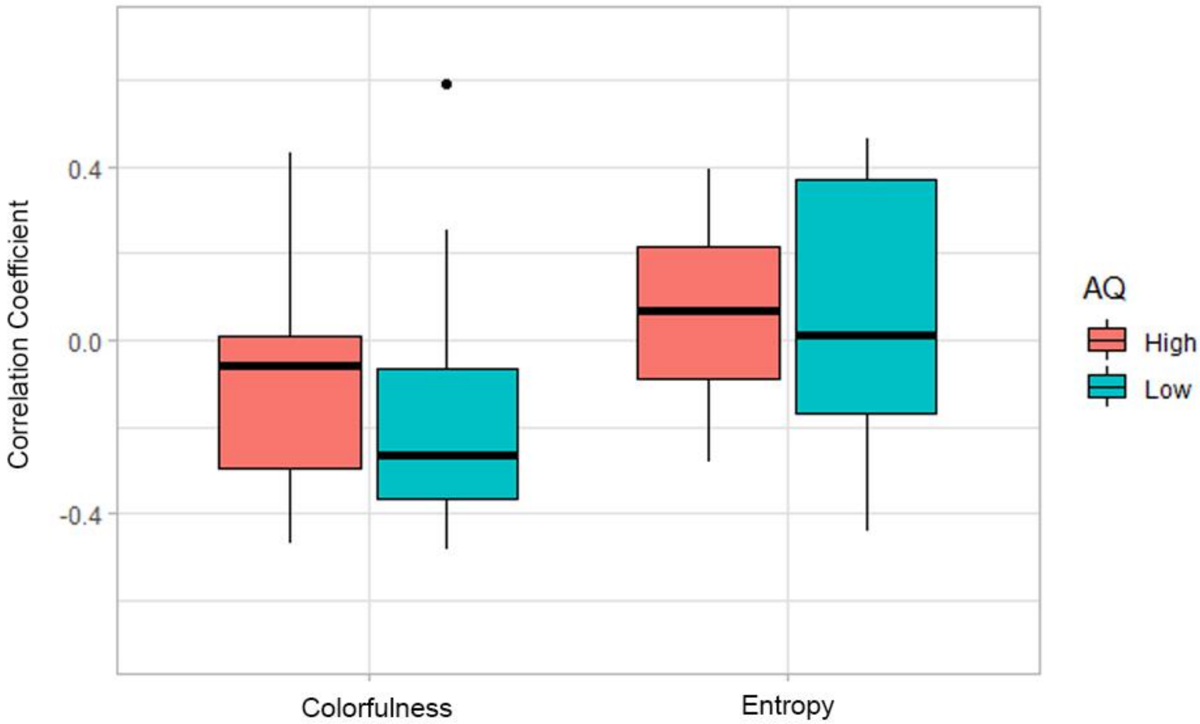

Figure 3.2 Boxplot of correlation coefficients between complexity algorithms and human subject mElo scores.

The distribution of correlation coefficients for low and high AQ groups and for colorfulness and entropy algorithms are shown. Both high and low groups had no significance for entropy correlations to human mElo ratings. Colorfulness correlations were significant in the low AQ group.

The mElo scores were averaged for each art category for low and high AQ participants. Because these Elo scores are based on rank orderings and designed to sum to zero, direct comparisons of these mElo scores between low and high AQ participants are not well-defined. However, we can use differences between pairs of art categories as the basis of comparisons between the low and high AQ participants. In separate analyses for preference and complexity, the difference between the mElo score was taken for pairs of art categories for each participant and then entered into a 2-sample t-test comparing the low and high AQ groups.

Complexity mElo Differences

		Representational - Face	Face - Abstract	Representational - Abstract
Low AQ	Mean Difference (SD)	-125.4 (152.9)	104.3 (304.4)	-21.1 (219.6)
High AQ	Mean Difference (SD)	-145.5 (148.3)	104.0 (251.7)	-41.5 (194.3)
	Low – High	20.1	0.3	20.4
	t(42)	0.44	0.003	0.32
	p	0.66	0.10	0.75
Low AQ	Representational - Face	---	t(24) = -2.68 p = 0.01	t(24) = -1.71 p = 0.10
	Face - Abstract	---	---	t(24) = 4.10 p = 4.1e-4
	Representational - Abstract	---	---	---
High AQ	Representational - Face	---	t(18) = -2.98 p = 0.01	t(18) = -1.80 p = 0.09
	Face - Abstract	---	---	t(18) = 4.28 p = 4.5e-4
	Representational - Abstract	---	---	---

Table 3.3 Complexity mElo Differences.

The mElo scores for perceived complexity were averaged for each art category for each subject. We looked at the difference between art categories and completed a 2-sample t-test on those differences between Low and High AQ groups (top portion of the table). The bottom portion of the table shows the upper-triangle for paired t-tests between the differences in mElo scores within Low and High AQ groups.

Table 3.3 summarizes how the mean differences in mELO scores, which are based the perceived complexity ratings for pairings of art categories, varied between low and high AQ groups. There were no significant differences for any of these comparisons.

However, for both low and high groups, the difference in scores Representational – Face differs significantly from that of the difference between Representational – Abstract. Furthermore, for both groups, the difference in scores Face – Abstract differs significantly from that of the difference between Representational – Abstract.

Preference mElo Differences

		Representational - Face	Face - Abstract	Representational - Abstract
Low AQ	**Mean Difference (SD)**	7.9 (146.9)	85.0 (223.8)	92.9 (192.8)
High AQ	**Mean Difference (SD)**	43.7 (185.2)	145.8 (235.2)	189.6 (169.7)
	Low – High	-35.8	-60.9	-96.7
	t(42)	-0.72	-0.87	-17.3
	p	0.48	0.39	0.09
Low AQ	**Representational - Face**	---	t(24) = -1.18 p = 0.25	t(24) = -1.90 p = 0.07
	Face - Abstract	---	---	t(24) = -0.27 p = 0.79
	Representational - Abstract	---	---	---
High AQ	**Representational - Face**	---	t(18) = -1.15 p = 0.27	t(18) = -2.70 p = 0.01
	Face - Abstract	---	---	t(18) = -1.03 p = 0.32
	Representational - Abstract	---	---	---

Table 3.4 Preference mElo Differences.

The mElo scores for preference were averaged for each art category for each subject. We looked at the difference between art categories and completed a 2-sample t-test on those differences between Low and High AQ groups (top portion of the table). The bottom portion of the table shows the upper-triangle for paired t-tests between the differences in mElo scores within Low and High AQ groups.

Similarly, Table 3.4 summarizes the analogous data for preference ratings. There were no significant differences for any of these comparisons. However, for both low and high groups, the difference in scores for Representational – Face differs significantly from that of the difference between Representation – Abstract. Even though the mean difference is greater in the high AQ group for Representation – Face, there is large variability; thus, there isn't enough evidence to conclude for this set of art pieces that low and high AQ groups differ from one another for their preference ratings of these art categories.

There are a few caveats regarding the failure here to find differences in the patterns of preferences or complexity ratings between low and high AQ groups. The high variability of these differences may reflect other important differences between the specific art pieces that, because they are unidentified, are not controlled in this experiment. This is one of the major challenges in empirical aesthetics where art pieces are not something easily controlled because they were created by other people. Art pieces themselves are not stimuli that are generated by a program we can control in terms of their extrinsic properties. We can identify and categorize art pieces according to their extrinsic properties like how the art categories we had for this experiment. Also uncontrolled were differences in art expertise across observers; we did not actively seek out art experts the way that we sought out high and low AQ individuals. It is possible that there are other intrinsic properties that we have not taken into account that could have influenced the perceived complexity and preference for this set of art pieces.

We've observed that there isn't enough evidence to say that there is a reliable difference between how low and high AQ individuals rate these art categories in perceived complexity or preference. The next question we asked was whether complexity ratings predict preference ratings? Table 3.5a & 3.5b summarizes the Mann Whitney – U test on the preference and complexity mean differences for low and high AQ groups. For Face and Abstract art pieces, low and high AQ groups ranked these art pieces in a similar order for both complexity and preference. This is consistent with the premise that complexity and preference ratings mirror one another. Interestingly, the order of how these groups ranked Representation and Face art pieces for complexity is different than how they ranked the art pieces for preference. This observation is inconsistent with the strict notion that complexity directly determines preference ratings. However, this observation does not fully discount that complexity and preference are related via the set point theory.

a. Mann Whitney - U Low AQ Preference vs. Complexity

	Preference Mean	Complexity Mean	Z-value	p
Representational - Face	7.92	-125.37	3.01	0.003
Face - Abstract	84.98	104.31	-0.58	0.56

b. Mann Whitney - U High AQ Preference vs. Complexity

	Preference Mean	Complexity Mean	Z-value	p
Representational - Face	43.72	-141.45	3.2114	0.0013
Face - Abstract	145.84	103.99	0.6131	0.54

Table 3.5a & 3.5b Mann Whitney-U Table.

A Mann Whiney-U test was applied on the differences for Representational – Face and Face – Abstract for preference and complexity in low (3.5a) and high (3.5b) AQ groups.

The set point theory which is emphasized in the Hedonics model of the Aesthetic Experience states that a person can have an optimal point on a dimension such as complexity which will be the most preferred (Daniel E. Berlyne, 1970; Martindale, 1984). Figure 3.1 shows the how preference can vary as a function of complexity depending on where a person's set point is. For example, a person's set point could be on high complexity and thus, we will see high preference for high complex items and low preference for the medium and low complex items (Figure 3.1a). This relationship is a direct relationship that the Mann Whitney – U test was looking for; however, we did not see this relationship being consistent for our set of art pieces in this experiment. The set point theory also includes the inverse relationship of complex and preference shown in figure 3.1b, and it includes the inverse-U relationship shown in figure 3.1c when a person can have a set point in for medium complexity where preference will be the highest. Table 3.6 shows all the orderings of the different art categories for complexity and preference ratings, and we determined which subjects followed which orderings. Additionally, we coded which relationships were consistent with the set point theory and which were inconsistent (Table 3.6). For the low AQ group, 21 out of 25 participants had complexity and preference ratings that were consistent with the set point theory. Similarly, the high AQ group had 15 out of 19 participants that were consistent with the set point theory. While not every subject followed a strict model of complexity ratings equating preference ratings, most subjects do seem to have different set points for complexity and their preferences reflect that set point. Within low and high AQ groups, we see subset of individuals following a specific set point pattern, but we do not have a large enough sample to discern a particular pattern as to why these individuals have different set point patterns.

a.

Low AQ

Preference Order (Highest to Lowest)

Complexity Order (Highest to Lowest)	AFR	ARF	FAR	FRA	RAF	RFA
AFR	0	1	1	1	0	2
ARF	0	2	1	1	0	0
FAR	1	0	0	0	1	1
FRA	1	2	0	5	0	5
RAF	0	0	0	0	0	0
RFA	0	0	0	0	0	0

Direct Set Points	7	Set Point Impossible	4
Inverse Set Points	6	Other Set Points	8

b.

High AQ

Preference Order (Highest to Lowest)

Complexity Order (Highest to Lowest)	AFR	ARF	FAR	FRA	RAF	RFA
AFR	0	0	1	2	0	2
ARF	0	0	0	0	0	0
FAR	0	0	0	2	3	1
FRA	0	0	0	4	1	2
RAF	0	0	0	0	0	0
RFA	0	0	0	0	1	0

Direct Set Points	4	Set Point Impossible	4
Inverse Set Points	5	Other Set Points	6

Table 3.6a & 3.6b Possible and Impossible Set point combinations.

A chart of possible outcomes was created for ranking Representational, Face, and Abstract art categories indicated by “R,” “F,” and “A” respectfully. The different combination of rankings is shown from highest to lowest rank for perceived complexity (rows) and preference (columns). Direct set points refer to Figure 3.1a. Inverse set points refer to Figure 3.1c. Other set points refer to Figure 3.1b.

CHAPTER 5: CONCLUSION

This dissertation reports on three experiments that observed how extrinsic and intrinsic properties influence different aesthetic experience outcomes. Experiment 1 investigated how the implementation of blur affected the distribution of attention on visual art through a change blindness task. Experiment 2 examined how well salience models capture certain extrinsic properties on an art piece and how these salience models compare to human eye fixations and scanpaths. Experiment 3 investigated how an intrinsic property, the Autism Quotient (AQ), may influence evaluations of perceived complexity and preference and, more generally how preference judgements may be related to perceived complexity.

Experiment 1 investigated how blur implementation affects the distribution of attention on visual art through a change blindness task. The role of blur in an image is important in guiding spatial attention. Previous studies have shown that people tend to look at clear areas when blur is present (DiPaola et al., 2013; Enns & MacDonald, 2013; Khan et al., 2011). The reason why people tend to look at clear areas can be explained through the fluency model. While the fluency model tends to focus on preference as an outcome, this model primarily highlights the ease with which people process an image and how it affects an outcome. In our experiment, we identified salient areas of interest (AOIs) and applied blur in numerous ways in regards to these AOIs. The implementation of blur improved the accuracy of detecting changes only when it was applied to the whole art piece excluding the AOI. Having blur applied everywhere except at an AOI can make it easier for a person to identify what to look at in an art piece. Applying blur in this manner produces a drastic contrast in texture so that humans will naturally to look at the clear item first rather than the blurred items – it would take more effort to decipher what the blurred things are, so people may not want to look at those things right away. We also attempted to determine if there were differences between art experts and nonexperts in how their attention was affected by the different implementations of blur on an art piece. Although, there was not evidence in our data for a difference between art experts and nonexperts because of our small sample size, this is also not evidence against an effect of expertise. Previous studies have shown that art expertise has an influence on outcomes such as attention and preference (Koide et al., 2015; Pihko et al., 2011; van Paasschen et al., 2015). In the context of fluency theory, we may hypothesize that art experts may be influenced by blur differently than nonexperts because expertise is an intrinsic property that may make it easier for experts to explore and interpret nonsalient areas of an art piece compared to nonexperts.

Experiment 2 examined whether different people look at the same areas within an art piece and whether their scanpaths between regions were similar. Perceptual and cognitive models of the aesthetic experience emphasize how bottom-up and top-down processes of perception and cognition contribute to outcomes of the aesthetic experience. Redies (2015) parallel processing model highlights that both perception and cognition modulate one another in the aesthetic experience. Our results showed people look at similar regions, as previous studies have found. However, the scanpaths between these areas observed in this experiment were more similar across people than were reported in earlier studies; a key difference is that in this study the scanpaths came from the first viewings of an art piece whereas in the previous studies the participants viewed each art piece multiple times. Because the scanpaths were more similar between subjects, it is plausible to conclude that our subjects were relying more on extrinsic properties to guide their attention over the art pieces.

Experiment 2 also showed that salience models, based on the extraction low-level features, identified many regions of interests (ROIs) that were similar to those found in the human data; however, they did not assign salience to faces in art pieces as humans do. This suggests that humans rely heavily on extrinsic properties related to low-level features such as color, contrast, and orientation to guide their attention on the art piece. However, pairs of humans only tended to share about 50% of the regions that they looked at on art pieces which means that the other 50% were fixations made on unique regions for each person. People's unique fixations tell us that other factors such as intrinsic properties, which we did not account for, may influence the distribution of spatial attention. This reasoning is consistent with Redies' parallel processing model (2014) in which humans are not only using extrinsic properties to guide their attention, but they are also using top-down processes and intrinsic properties to explore the art piece. Additionally, this reasoning can extend to how scanpaths are more dissimilar for repeated viewings in other studies, in which top-down processes may become more dominant for repeated viewings and familiarity with an image.

One goal of Experiment 3 was to investigate the relationship of an intrinsic property, AQ, on perceived complexity and preference rating of art pieces. We did not observe a difference between low and high AQ individuals in how they rated perceive complexity or preference for the set of art pieces we had used. This experiment also investigated the relationship between perceived complexity and preference, and specifically whether a set point mechanism, predicted by the hedonics model, could explain the discrepancies in this relationship observed in earlier studies. Consistent with this proposal, the preferences for almost all of the observers were consistent with a complexity set point. There was not a clear set point that either low or high AQ individuals followed greatly; their set points for perceived complexity and preference varied. Although the complexity set point for some observers was at either the high or low end of the complexity scale, and thus were consistent with simpler models, many more of the set points were not at either end of the complexity scale and so, for these observers the observed preferences violated the simpler models. These observers had varied set points for complexity and preference which could be explained with other intrinsic properties we did not account for in this experiment, and the nature of the differences between set point remains to be explored more deeply.

The aesthetic experience includes many facets with the different independent and dependent variables that can be identified in empirical aesthetics research. Research into the aesthetic experience is still in its infancy. Reflecting this, the existing studies approach the aesthetic experience from different perspectives, tackling a variety of questions using different measures of the aesthetic experience. The experiments reported here corroborate the findings from previous studies that both extrinsic and intrinsic properties influence the outcomes of the aesthetic experience, and that the relationship between these properties can be complex, such as the set points that we observed in Experiment 3. The aesthetic experience is unique to each individual, and we have much to explore about the intricate relationship that exists between extrinsic and intrinsic properties that form this unique experience.

These experiments also show the difficulties of studying the aesthetic experience using art as experimental stimuli. Art pieces themselves have a number of factors that are difficult to control because each art piece was created by a person, the artist, who brings their own intentions of what they want to portray. Because artists have at least some understanding how humans perceive and interpret art, and they use will that knowledge to their advantage to create art pieces that build on the viewers' perceptions (Arnheim, 1965; Cavanagh, 2005). Even though visual art stimuli offer these complications, they are valuable in our investigations of the aesthetic experience and our understanding of how human explore and interact with a stimulus that is another person's creation. The findings from empirical aesthetics and neuroaesthetics can prove useful for real world application of marketing and designing products that people encounter.

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APPENDIX A

All art pieces presented in the figures of this dissertation belong to the author of this dissertation under the pseudonym *dra9onsart*. All other art pieces used in our experiments are cited here.

Deviantart Art Pieces:

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