PEOPLE AND PRODUCTS:
IS THERE A SYNERGISTIC RELATIONSHIP?

A Thesis

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ABSTRACT

The present study was conducted to investigate 1) how the presence and attractiveness of a human model along with a product influences the attractiveness ratings of the image; 2) whether pupil area can be used as an objective measure of image attractiveness; 3) whether image complexity systematically affects eye movements; and 4) whether there are gender or designer status differences in viewing patterns. In this study, eye tracking software was utilized to capture pupillary responses, fixation durations, number of fixations, and areas of focus represented by heatmaps and lookzones. Results showed that the presence of a human model increased perceived overall image attractiveness. Image model attractiveness increased linearly with model attractiveness. Pupils dilated when viewing images with human models present, and decreased when viewing images without human models. However, changes in pupil area were not significantly associated with image attractiveness. Results also confirmed that fixation duration increased and the number of fixations decreased as image complexity increase with the presence of a human model. There were significant designer status differences in average fixation time, number of fixations, and areas of focus. Designers had more, shorter fixations when viewing simple images and fewer, longer fixations when viewing moderately complex images compared to non-designers. Additionally, there were significant gender differences in image attractiveness ratings and number of fixations when a

human model was present. Females rated images without a model more attractive and had fewer fixations compared to males, whereas males rated images with a model more attractive and had fewer fixations compared to females.

BIOGRAPHICAL SKETCH

Jordan Licero is a graduate student in Cornell University's department of Design and Environmental Analysis, concentrating in Human Factors and Ergonomics. Jordan completed her high school education in 2008 from Darien High School (Darien, CT). She graduated with a Bachelors of Science with Honors from Cornell University in 2012.

For my family, who provides infinite support, motivation, and encouragement.

Thank you for always believing in me and ensuring I never give up on my passion.

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CHAPTER 1: LITERATURE REVIEW

1.1 Introduction

Ergonomic, design, and architecture magazines and advertisements seldom use images of products or interior spaces with human models (Dion, Berscheid, & Walster, 1972; Petroshius & Croker, 1972). Yet the presence of a human face or a human model in an image has been shown to be more attractive to the viewer than those without (Nielsen & Pernice, 2010). The present study extends on previous work by investigating whether the presence of a human model used to increase image complexity and the attractiveness of the human model beside a product creates an even more attractive image. It also assesses the value of eye movements and pupillometry as objective measures of attractiveness.

1.2 Attraction

Although the concept that *beauty sells* has directed some advertisers to hire attractive spokespeople and human models to represent their products in print and television advertisements, evidence of their impact has been inconclusive (Caballero & Pride, 1984; Caballero & Solomon, 1984; Dion et al., 1972). While some previous studies have found that attractiveness of a human model in an image along with a product increases product sales (Caballero & Pride, 1984; Dion et al., 1972), other studies have found no effect of an attractive human model on product sales (Caballero & Solomon, 1984). However, there is no empirical evidence yet that directly found that an attractive human model increases overall image attractiveness. Prior studies have only analyzed product sales, rather than evaluating the attractiveness of the image itself or the human model itself. In order to determine whether a human model impacts the perceived attractiveness of an overall image, it is first necessary to understand what is considered attractive and why.

1.2.1 Attractiveness and the Human Face

Research has identified specific characteristics associated with the attractiveness of human models (Nielsen & Pernice, 2010). Smiling faces have been shown to be attractive to babies, and they continue to be attractive to people throughout adulthood (Nielsen & Pernice, 2010). Images of people with their faces looking directly into the camera have been shown to draw more attention compared to people looking in other directions, and those who are genuinely attractive, attract more viewers, compared to unattractive or fake-looking people (Nielsen & Pernice, 2010).

Human brains have evolved to be sensitive towards facial attractiveness, and the human brain possesses regions responsible for processing facial attractiveness (Blackburn & Schirillo, 2012; Winston, O'Doherty, Kilner, Perrett, & Dolan, 2007; Aharon et al., 2001; Kowner, 1995). Kowner (1995) proposed the right-hemisphere hypothesis, which suggests the right hemisphere of the brain dominates in the perception and expression of emotions, regardless of the valence of emotions. In Kowner's (1995) study, when left and right sides of the face were simultaneously compared, the left side of the face showed greater activity when participants viewed smiling faces, but not when participants viewed neutral faces. A study by Blackburn and Schirillo (2012) investigated this hypothesis and found that regardless of whether the visual stimulus was an original image or mirror-reversed image, left-sided portraits, which are processed by the right hemisphere, were preferred over right-sided portraits, which are processed by the left hemisphere (Blackburn & Schirillo, 2012). Further affirming the left-side preference, a study analyzing 1,474 Western European portraits found that the majority of posers (~64%) exposed their left cheeks while only approximately 33% exposed their right cheeks (McManus, 2005). Therefore, in general, people prefer to look at visual images of a person's left side of the face to the right side (Blackburn & Schirillo, 2012; Kowner, 1995).

1.2.2 Reward Regions of the Brain and Facial Attractiveness

Facial attractiveness is an important variable in mate choice in that it denotes biological advantages such as mating success, earning potential, and longevity (Winston et al., 2007). A study by Aharon et al. (2001) used functional magnetic resonance images (fMRI) to obtain detailed anatomical information of each participant while viewing stimuli of human faces. Functional magnetic resonance images measure brain activity by detecting associated changes in blood flow.

Behavioral data from Aharon et al.'s (2001) study showed that heterosexual males make an effort to observe attractive female faces, but not to observe unattractive female faces or any male face. In addition, behavioral evidence from heterosexual male participants indicated viewing attractive faces activated five brain rewards regions: the nucleus accumbens, sublenticular extended amygdala of the basal forebrain, amygdala, orbitofrontal cortex, and the ventral tegmentum of the midbrain (Aharon et al., 2001).

To further explore how attractive faces activate reward regions, Winston et al. (2007) asked participants to rate stimuli of human faces as either highly attractive, medium, or highly unattractive. Similar to Aharon et al.'s (2001) study, Winston et al. (2007) used fMRI scans to study the relationship of brain response and facial attractiveness. The results showed a response to facial attractiveness in the orbitofrontal cortex, which is involved in cognitive processing of decision-making, including emotion and reward in decision-making. Additionally, the right amygdala, an area in the medial temporal lobes that processes memory and emotional reactions, showed a predicted non-linear response with greater responses to highly attractive and highly unattractive faces compared to faces ranked as middle attractiveness. Furthermore, findings suggested the medial prefrontal cortex, insula, and superior temporal sulcus were activated during attractiveness judgments. These findings suggest that neural responses to facial attractiveness are automatically engaged and that reward regions are activated when judging highly attractive human faces (Winston et al., 2007).

Given that both studies indicated an activation of the reward regions of the brain when participants viewed attractive faces, it is possible that images that include attractive faces elicit more positive reactions and higher attractiveness ratings of overall image attractiveness.

1.2.3 Attractiveness and Aesthetics

Helander (2010) explored the relationship between the aesthetic qualities of an object, and perceived attractiveness. Specifically, he found that the perceived comfort of a chair in an image was independent of its ergonomic features, but dependent on ratings of the attractiveness of its aesthetic design (Helander, 2010).

Nagamachi (2001) studied consumers' perceptions of aesthetics in order to develop highly sought-after products. Consumers' psychological feelings and perceptions of aesthetics were derived from questionnaires about expectations, desires, and current attitudes towards similar products or prototypes. When the consumers' feelings of the aesthetics of a product were integrated into the design, the products were deemed more attractive, which led to greater success of the new products on the market (Nagamachi, 2001).

The aesthetic design of a product strongly contributes to the consumer's pleasure derived from the product (Jordan, 1997). Users self-reported that both style and color are important aesthetics factors. A product provided with the user's choice of color and style often made that product more attractive and pleasurable to the user; while the lack of aesthetic appeal often contributed to making a product less attractive and displeasurable to the user (Jordan, 1997).

1.2.4 Berlyne's Aesthetic Theory

Based on viewers' self-evaluated judgments of pleasure and the relation to the arousal potential of a stimulus, Berlyne (1974) developed his aesthetic theory, which predicts that aesthetics play a significant role in the arousal potential and pleasingness of an image. The relationship between aesthetics and pleasure is represented by an inverted U-shaped curve, intersected by a linearly increasing line for arousal potential of stimuli. Berlyne suggested moderate arousal stimuli are pleasurable, while low arousal stimuli are boring and high arousal stimuli are unlikable (Berlyne, 1974).

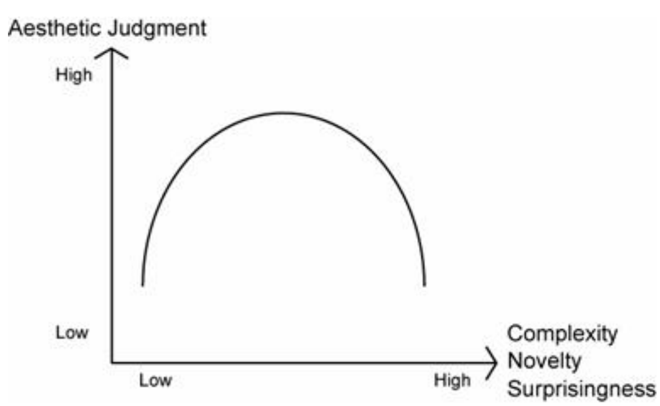

Figure 1.2.1: The relationship between image arousal and aesthetic judgments (Berlyne, 1974)

Image complexity has also been suggested to significantly influence judgments of interest and pleasure derived from the visual image (Berlyne, Ogilvie, & Parham, 1968). In Berlyne et al.'s study (1968), participants were asked to rate the complexity, pleasingness, and interestingness of a series of images. Results showed that interest and pleasure are significantly related to image complexity, and image complexity is a function of the number of objects in the image (Berlyne et al., 1968). Therefore, the addition of a human model in a product image increases complexity, and thus, should increase attractiveness ratings. However, it is still unclear how the presence of a human model used to modify image complexity and how the attractiveness of a human model affects overall perceived image attractiveness.

Geissler, Zinkhan, and Watson (2006) examined the influence of the perceived homepage complexity on communication effectiveness, measured by attention to the homepage, attitude towards the homepage and company, and intent to purchase from the homepage. Results indicated that homepage complexity did influence communication: moderate complexity was the most effective in maintaining consumer attention and eliciting the most positive first impression from viewers (Tuch, Bargas-Avila, Opwis, & Wilhelm, 2009; Geissler et al., 2006; Berlyne, 1974). Therefore, further understanding of how increased image complexity through the presence of an additional person in a visual image alters eye movement patterns and perceived attractiveness may lead to an even more positive first impression from the viewer (Olivia, Mack, Shrestha, & Pepper, 2004; Berlyne et al., 1968).

1.2.5 Advertising and Attractiveness

Some studies found the presence of a physically attractive human model increases the effectiveness of an advertisement (Petroshius & Croker, 1989; Caballero & Pride, 1984), another study has found the influence of a physically attractive human model on an advertisement depends on the product being advertised (Trampem, Stapel, Siero, & Mulder, 2010), while others have found unattractive human models influence the effectiveness of an advertisement more positively than attractive human models (Caballero & Solomon, 1984).

Petroshius and Croker (1989) assessed the impact of the physical attractiveness, sex and race of a spokesperson on television, the sex of the respondent, and finally the respondent's perception of the advertised product. Results showed physical attractiveness of the spokesperson increased advertisement ratings in terms of interest and eye-catching, but not in measures of product quality or product information, such as believable or informative (Petroshius & Croker, 1989).

Caballero and Pride (1984) used direct mail advertisements to study whether sex and attractiveness of a human model influenced the receiver's decision to purchase the advertised product. Direct mail advertisements were found to sell more products when the advertisements featured a highly attractive female model (Caballero & Pride, 1984).

Trampe, Stapel, Siero, and Mulder (2010) showed that the relevance of the attractive human model for an advertised product determine the effectiveness of the advertisement. For example, when advertising a diet product, which is a product where attractiveness was deemed relevant, an attractive human model had a greater impact on the advertisement effectiveness. However, when human model attractiveness is less relevant to a product, such as deodorant, the impact of an attractive human model did not affect attitudes toward the product. Therefore, the product was a confounding factor of the impact of an attractive human model on the advertisement effectiveness (Trampe et al., 2010).

In contrast, Caballero and Solomon (1984) failed to show any significant impact of physical attractiveness on advertising effectiveness. Pictures of attractive male and female models using either facial tissues or holding a beer were positioned near the advertised product in a store. Results suggested that for beer, there was no difference in consumer's purchases due to the human model's attractiveness. However, for facial tissues, the presence of the low attractive human model sold significantly more facial tissues than other human models with higher attractiveness levels (Caballero & Solomon, 1984). These opposing results may also be due to a product difference. The items chosen for this study were items consumers likely already intended to purchase when visiting the store; thus, they may have bought the items regardless of the advertisement (Caballero & Solomon, 1984). Furthermore, it is unclear whether consumers viewed the advertisement of the product with the human model at all.

The inconsistent findings from these four studies may have arisen because they utilized different advertisement delivery methods, promoted different products, and utilized different measures for capturing the influence of an attractive spokesperson or attractive human model on advertisement attractiveness or product sales. Given the lack of various controls and the dissimilar findings of these studies, further research is needed to determine the power of human presence and attractiveness over image attractiveness and product sales.

Studies evaluating the attractiveness of the human model have been limited to print and television advertisements, not web advertisements. Unlike print and television advertisements, web advertisements can allow the user to directly click the visual image to further explore the product being promoted; thus, capturing the consumer's attention is perhaps even more important for product sales and promotion. Additionally, understanding how to capture the consumer's attention on the web is becoming increasingly important as we expend more of our time each day to web-use (Nielsen & Pernice, 2010).

1.3 Physiology of the Human Eye

Finding an objective measurement of the perceived attractiveness of human models in an image may allow for a better way to select appropriate human models, in order to more effectively promote an ergonomic product or indoor space (Laeng, Sirois & Gredeback, 2012; Watson & Yellott, 2012). Research has shown that patterns of eye movements are affected by both the aesthetic properties of the visual image being scanned as well as by cognitive processes such as expectations (Laeng et al., 2012; Watson & Yellott, 2012; Harper, Michailidou, & Stevens, 2009). However, to understand how eye measurements can be used to derive information about visual processing, first it is important to understand the physiology of the human eye.

1.3.1 Human Eye Structure

The human eye is a slightly asymmetrical sphere (~24 to 25 mm diameter) that allows us to capture external visual information by processing the light reflected or emitted by the external visual stimulus being viewed (Cunningham, 2011). The human eye comprises three major layers of tissues and three fluid chambers (Saladin, 2012; Cunningham, 2011). Refer to Figure 1.3.1 below for a visual of an adult human eye with labels for the individual parts of these three major layers of tissues. The outermost layer comprises the cornea and the sclera (Saladin, 2012). The sclera is the white of the eye, which is roughly $5/6^{th}$ of the eye surface, while the cornea is the clear dome located over the colored part of the eye, the iris, and it comprises the other

$1/6^{th}$ of the external surface of the eye (Saladin, 2012). The sclera and cornea serve to protect the inner parts of the eye from the exterior environment (van de Pol, 2009). The cornea is also used to focus light entering the eye (Saladin, 2012; van de Pol, 2009).

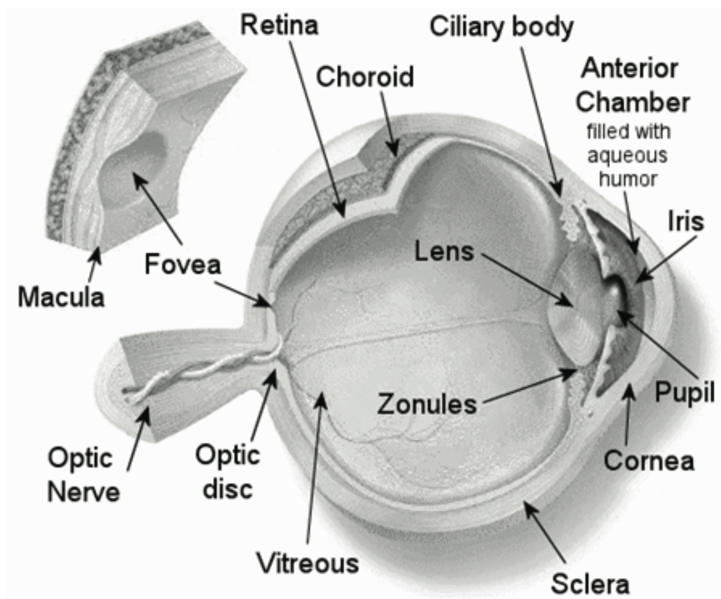

Figure 1.3.1: Sagittal Section of the Adult Human Eye (van de Pol, 2009)

The middle tissue layer is divided into two parts: anterior (iris and ciliary body) and posterior (choroid) (Saladin, 2012). The ciliary body protects the lens and helps to change the lens shape to modify the eye's focus point (Cunningham, 2011). The iris is the colored part of the eye, which may be a shade of blue, brown, green, grey, or some mix of those colors (Laeng & Endestad, 2011). The iris absorbs light and protects the retina, which is the sensitive part in the back of the eye, from excessive light (Laeng & Endestad, 2011). In the center of the iris, which is a muscle, is an opening: the pupil (Cunningham, 2011). Iris muscles make the pupil constrict or dilate, which allows the pupil to vary in diameter typically between 1.5-9 mm, which happens in response to changes in light level and the emotional state of the person (Andreassi, 2007). The choroid is the thin fibrous connective tissue layer that is located beneath the sclera (Cunningham, 2011). This layer consists of many blood vessels that are used to transfer nutrients and oxygen to the innermost layer in the back of the eye (Cunningham, 2011).

The innermost layer consists of the retina, which is the highly specialized sensory tissue of the eye, where the initial processing of visual information occurs (van de Pol, 2009). Light entering the eye strikes the macula, the furthest region of the retina. Vision is sharpest when light is focused in the fovea, which is a small retinal region at the center of the macula with the greatest density of photoreceptors (van de Pol, 2009). There are two types of receptors in the retina: rods and cones, which are so called for their shape (Cunningham, 2011). There are approximately 5 million cones and 92 million rods in the normal adult retina (van de Pol, 2009). Cones enable the eye to discern color and see fine detail in daylight, while rods are mainly responsible for vision in low light conditions (Cunningham, 2011; van de Pol, 2009).

Three fluid chambers affect the shape of the eye. There is an anterior chamber between the cornea and iris, a posterior chamber between the iris and lens, and the vitreous chamber between the lens and the retina (Cunningham, 2011). The anterior and posterior chambers are filled with a watery aqueous humor, while the vitreous chamber is filled with a more viscous fluid, the vitreous humor (Saladin, 2012). The aqueous humor is fortified blood plasma and is responsible for providing nutrients to the cornea, as well as playing a role in the optical pathway of the eye (van de Pol, 2009). The vitreous humor is a clear gel that is loosely attached to the retina around the optic nerve and macula in order to maintain the shape of the eye; it makes up 80% of the volume of the eye (Cunningham, 2011; van de Pol, 2009). These structures and fluids of the eye all work together to produce an image of incident light that can ultimately be interpreted in the brain (Saladin, 2012).

1.3.2 Visual Processing

The visual process starts when light waves from an object enter the eye through the cornea. As light passes through the cornea the light waves converge due to the curvature of the cornea and the change in refractive index. The light then progresses through the pupil, which determines how much light enters the eye by constricting or dilating (Laeng & Endestad, 2011).

Further convergence is achieved by the crystalline lens, which changes shape, a process called accommodation, to focus the light on the macula (Saladin, 2012). This process inverts and reverses the visual image (Saladin, 2012). Within the macula, the highest resolution occurs when light is focused on the fovea (van de Pol, 2009). Photons arriving at the photoreceptors in the retina initiate a biochemical process that causes membrane depolarization, which results in an electrical signal to intraretinal processing cells, the retinal ganglion cells, and these cells project axons to the optic nerve (Cunningham, 2011). The optic nerve of each eye consists of approximately 1 million retinal ganglion cell axons, which continue posteriorly and meet at the optic chiasm (van de Pol, 2009). It is at the optic chiasm that axons of neurons from the nasal retina (temporal visual field) cross to the contralateral optic tract, so axons from the right eye temporal visual field cross to the optic tract on the left side of the brain. However, axons of neurons from the temporal retina (nasal visual field) continue along the ipsilateral optic tract (van de Pol, 2009). Each optic tract projects signals to its lateral geniculate nucleus (LGN) in the dorsal thalamus (van de Pol, 2009). From the LGN, signals continue to the primary visual cortex, where further visual processing occurs (Cunningham, 2011). Once the electrical impulses make it to the occipital cortex, the signals are interpreted as a visual image (Saladin, 2012).

There are six separate areas in the visual cortex that are responsible for the final processing of the neural signals from the retina: V1, V2, V3, V3a, V4, and V5 (van de Pol, 2009). The primary visual cortex (V1) is where neural signals are interpreted in terms of visual space, such as form, color, and orientation of objects (van de Pol, 2009). The signals then pass through to V2, which is where color perception occurs and form is further interpreted. As the neural signals travel to other areas of the visual cortex, more processes take place to interpret the visual image. In the parietal visual cortical areas, motion of objects, motion of self with respect to object, and spatial reasoning are interpreted and perceived. In the temporal visual cortical area, including V5, recognition of objects through processing and interpretation of complex forms and patterns occurs (van de Pol, 2009). The final stage of processing a visual image is based on the psychological and perceptual experience of visual image, such as memory and expectations, conducted by non-visual areas of the brain (Nielsen & Pernice, 2010; van de Pol, 2009; Maw & Poplun, 2004).

Cognitive processing is required to interpret a visual stimulus, and the brain allows humans to "see" a visual image (Saladin, 2012; Cunningham, 2011; van de Pol, 2009).

1.3.3 Peripheral, Parafoveal, and Foveal Vision

There are three zones of human visual field: foveal, parafoveal, and peripheral vision. All three types work together to produce an entire visual image of objects in the field of vision of each eye (Nielsen & Pernice, 2010; Calvo & Lang, 2005). Visual acuity is maximal in the fovea, which is the central retinal area from 0 to 2 degrees and consists of only cone photoreceptors and no rods (Calvo & Lang, 2005). The high cone density enables the eye to discern color and to see fine detail (van de Pol, 2009). Foveal vision draws the highest level of attention (Calvo & Lang, 2005).

The parafovea is the region surrounding the fovea, extending 2 to 10 degrees from the fovea (Cunningham, 2011; Nielsen & Pernice, 2010). Parafoveal vision has lower acuity than foveal vision (Cunningham, 2011). This area of the retina has both cone and rod photoreceptors present, enabling color and grayscale to be seen (Calvo & Lang, 2005).

Peripheral vision, which extends beyond the parafoveal boundaries, is of even lower resolution and acuity than foveal or parafoveal vision (Calvo & Lang, 2005). The periphery of the retina has a low density of cones and a high density of rods, which allows humans to see in dim lighting (Calvo & Lang, 2005).

1.3.4 Extraocular Muscles

The extraocular muscles are responsible for controlling movements of the eye (Cunningham, 2011). There are three antagonistic pairs of muscles (6 muscles total) that control eye movements: the lateral and medial rectus muscles, the superior and inferior rectus muscles, and the superior and inferior oblique muscles (Saladin, 2012). The medial and lateral rectus muscles control all horizontal eye movements (left and right movements); the medial rectus muscle is responsible for adduction, while the lateral rectus muscle is responsible for abduction. Vertical eye movements (up and down movements) involve a coordination of the superior and inferior rectus muscles (as well as the oblique muscles). The relative contribution of the rectus and oblique muscle groups depends on the horizontal positioning of the eye (Saladin, 2012). For example, if the eyes are looking straight ahead, both the rectus and oblique muscle groups contribute to the vertical movements. When the eye is abducted, the rectus muscles play a primary role in vertical movements and when the eye is adducted, the oblique muscles play a primary role in vertical movements (Saladin, 2012). Additionally, the oblique muscles are primarily responsible for torsional movements, which are inward and outward movements to counteract head movements (Cunningham, 2011). These six muscles work in unison to move the eye. As one muscle from a pair contracts, the opposing muscle relaxes, creating smooth eye movements (Cunningham, 2011). In addition to the muscles of one eye working in unison, the muscles of both eyes work together in a coordinated effort so that the eyes are always aligned (Cunningham, 2011; Nielsen & Pernice, 2010).

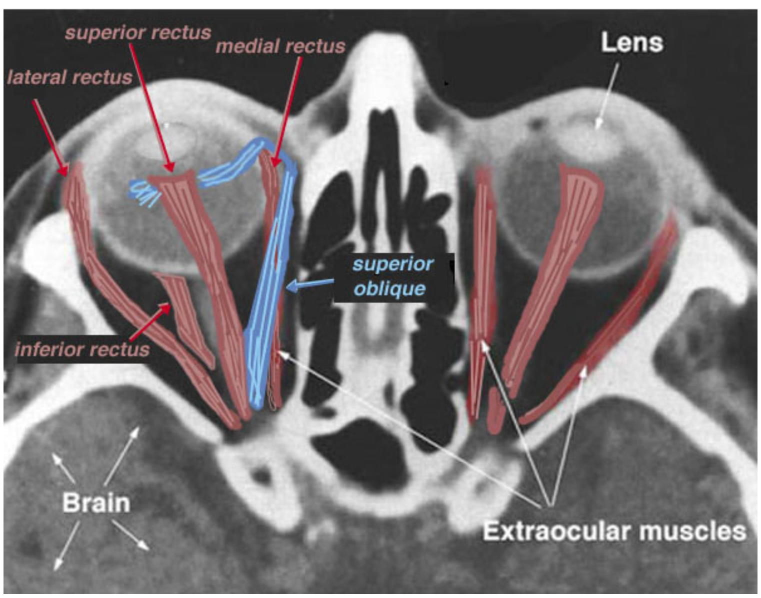

Figure 1.3.2: Extraocular Muscles of the Human Eye (Kolb, Fernandez, & Nelson, 2012)

1.3.5 Vergence and Accommodation

The simultaneous movement of both eyes in opposite directions is referred to as a vergence (Cunningham, 2011). For example, to look at an object closer to the viewer, the eyes rotate towards each other (convergence), while the eyes rotate away from each other (divergence) when the object is farther from the viewer (Cunningham, 2011; Cutting, 1997). Vergence movements automatically occur when a change the focus of the eyes is needed to look at an object at a difference distance (Cunningham, 2011; Cutting, 1997).

Similar to vergence movements, accommodation of the eye occurs automatically and instantaneously to refocus the visual image of an external object on the retina (Cunningham, 2011). The eye accommodates for close vision by contracting the ciliary muscles, allowing the pliable crystalline lens to thicken and increase in convexity (Saladin, 2012). This increase in convexity reduces the focal length of the lens, which allows the lens to focus on objects near and keep the retinal image sharp, while objects at other distances become blurred (Cunningham, 2011; Cutting, 1997). Humans vary the degree to which the lens can converge or diverge (optical power up to 15 diopters) light rays by changing its form (Saladin, 2012). The lens is suspended by ligaments, called zonule fibers, which are attached to the anterior portion of the ciliary body (van de Pol, 2009). The contraction or relaxation of the ciliary muscle tightens or loosens these ligaments, which in turn changes the shape of the lens, allowing the image to be focused on the fovea (van de Pol, 2009).

1.3.6 Eye Movements: Fixations and Saccades

Because of the small foveal field, in order to scan a large visual field the eyes have to move around the scene; for very large scenes, the head also moves. As the eyes scan a scene, the eye movements are composed of both fixations and saccades (Buscher, Cutrell, & Morris, 2009). A fixation is defined as a relatively motionless gaze at a specific area on a visual display and lasts about 200-300 milliseconds (ms) (Rayner, 1998). Saccades are continuous, rapid movements between fixation points that direct an individual's eye to a specific area, where the fixation is taking place (Smith, Levin, & Cutting, 2012; Rayner, 1998). Visual information is generally only perceived during fixation periods, not during saccades (Buscher et al., 2009). In a number of studies, fixation points have been associated with cognitive processing (Cutrell & Guan, 2007; Pan et al., 2004; Petersen & Nielsen, 2002). According to Viviani (1998), at least three processes take place during a fixation: encoding of a visual stimulus, skimming the peripheral field, and preparing for the next saccade to take place.

Many studies have also been conducted to examine where and when users will fixate on an image (Buscher et al., 2009; Pan et al., 2004; Rayner, 1998). A study by Rayner (1998) showed that eyes are attracted to specific areas that are generally physically distinctive or informative. Fixation frequency is dependent on the degree of importance or attraction, whereas fixation duration depends on the complexity (based on number of objects in a visual image) and difficulty of the visual display (Buscher et al., 2009; Pan et al., 2004; Olivia et al., 2004; Rayner, 1998;).

Longer and/or more fixations indicate the viewer spends more time to analyze the image and form an opinion on it. Additionally, fixations are associated with cognitive processing (Cutrell & Guan, 2007; Pan et al., 2004; Petersen & Nielsen, 2002; Viviani, 1998; Berlyne et al., 1968) and therefore, understanding eye movements, including the number, duration, and location of fixations, can indicate how the image was viewed and cognitively processed.

1.3.7 Iris Muscles

Two muscles in the iris are used to increase or decrease the size of the pupil: the sphincter pupillae (circular muscle fibers) and the dilator pupillae (radial muscle fibers) (Watson & Yellott, 2012; van de Pol, 2009). When the sphincter pupillae are activated, the iris increases in size and the pupil constricts to restrict light entering the eye (Cunningham, 2011). The sphincter response is activated by the parasympathetic nervous system, which is the system that regulates our autonomic physical processes when at rest (Laeng & Endestad, 2011). The Edinger-Westphal nucleus, which is an area in the midbrain responsible for constricting the pupil, contains the parasympathetic fibers (Kozicz et al., 2011). The parasympathetic fibers project along the oculomotor nerve to the ciliary ganglion near the eyeball, and finally to the smooth sphincter pupillae surrounding the pupil (Andreassi, 2007). On the other hand, the dilator pupillae are stimulated by the sympathetic nervous system in order to enlarge the pupil size to let more light into the eye (Cunningham, 2011; Laeng & Endestad, 2011). The sympathetic fibers in the hypothalamus region of the brain are projected downward to the spinal cord and leave the cord to synapse the superior cervical ganglion, which projects the sympathetic influence to the dilator pupillae of the iris (Andreassi, 2007).

Given that the autonomic nervous system is involved in emotional behavior, and that pupillary responses are partially under autonomic nervous system control, pupillary responses have been suggested to reflect emotional reactions to an image being viewed (Laeng et al., 2012; Watson & Yellott, 2012; Andreassi, 2007). These pupillary reactions to a visual image can occur in as little as 0.2 seconds, with the response peaking from 0.5 to 1.0 seconds (Andreassi, 2007; Lowenstein & Loewenfeld, 1962). The pupil can constrict to a diameter of 1.5 and can dilate to a diameter of approximately 8 to 9 mm; however, the average pupil area varies across individuals (Watson & Yellott, 2012; Andreassi, 2007; Lowenstein & Loewenfeld, 1962).

1.4 Pupillometry & Pupillary Reactions

Pupillometry is the measurement of the pupil's diameter as it reacts to various stimuli (Andreassi, 2007). Though pupillometry is typically a measure of the pupil's diameter, software often calculates pupil area, both of which have been measures used to determine pupillary dilations or constrictions (Andreassi, 2007). Vertical pupil diameter has been found to be only slightly larger than horizontal pupil diameter in most people (Khanani, Archer, & Brown, 2004). However, the difference is such a small fraction of the total pupil diameter that either can be used for pupillometry. Additionally, only the diameter or area of one pupil is necessary to determine these pupillary responses because the changes in pupil size occur simultaneously in both eyes (Andreassi, 2007).

Given that the pupillary reactions to a visual image occur in as little as 0.2 seconds and have a peak response anywhere from 0.5 seconds to 1 second, pupillary measures are often taken for greater than 1 second time periods to ensure the peak pupillary reaction measurement is captured (Andreassi, 2007; Lowenstein & Loewenfeld, 1962). These measurements are typically averaged over the length of time to prevent bias and provide more accurate pupillary measurements (Lehman, O'Rourke, Hatcher & Stepanski, 2013). The peak of the pupillary reaction may vary based on a number of different factors such as blinks or positioning of the camera (Gagl et al., 2011; Privitera, Renninger, Carney, Klein, & Aguilar, 2008). However, it is impossible for humans to suppress a pupillary dilation or constriction at will, regardless of whether the pupil area change was evoked by an external factor or mental events (Loewenfeld, 1993). Pupillometry provides a "window to the preconscious" (Laeng et al., 2012, p. 18), as it captures a person's initial, objective reaction to a particular visual stimulus (Andreassi, 2007). Pupillometry is now being used to obtain objective measures of emotional responses to given images (Laeng et al., 2012).

1.4.1 Emotional Valence and Interest

The idea that larger pupils indicate attraction to whatever is being viewed dates back thousands of years (Swaminathan, 2008). In the Middle Ages, Italian males viewed dilated pupils as more feminine and more attractive. Thus, Italian females used belladonna, a drug prepared from the roots and leaves of the deadly herb nightshade, to draw back the irides and increase pupil area (Swaminathan, 2008); bella donna means "beautiful woman" in Italian.

In 1965, Hess asked males to compare the attractiveness of images of females with average pupil size to drawings where the female's pupils were enhanced. Consistently, males rated females with enhanced pupils as more attractive compared to females with average pupil size (Hess, 1995). Tombs and Silverman (2002) demonstrated that, unlike males, females preferred medium-size pupils to dilated pupils in males; the study concluded this was because medium-size pupils indicated interest but not blinding lust. Males, on the other hand, preferred females with dilated pupils, because large pupils were an indication of sexual attraction on the female's part (Tombs & Silverman, 2002).

One of the most influential studies using pupillometry was conducted by Hess and Polt in 1960. Although this study was not the first to indicate the possibility of the relationship between pupil area and emotional valence, their work led to increased activity in this area by psychologists and researchers (Andreassi, 2007). When viewing pictures of a nude male and of a baby, female participants showed larger pupil dilation responses than males. However, males showed larger pupil dilation responses compared to females when viewing a picture of a nude female (Andreassi, 2007). These results showed that pupil area increased when viewing an emotionally toned or interesting visual stimulus. However, the visual stimuli used in Hess and Polt's (1960) study were primarily people; hence, the results cannot necessarily be extrapolated to images of inanimate products. Also, there were only a few subjects (n=6), who viewed images for 10 seconds, which goes beyond the period of time needed to capture the pupils' initial reaction to the image (Hess & Polt, 1960). To measure pupil size, Hess and Polt (1960) used a Percepto-scope, which is a device that consists of a 16-mm camera to film the pupil, a projector and screen to magnify the image, and a ruler to measure the vertical pupil diameter by hand. Because these pupillary changes were measured by hand, it is likely that there was measurement error in the data (Lowenfeld, 1999).

More recently, Blackburn and Schirillo (2012) found that pupil dilation occurred when viewing the left-side of the face compared to the right-side of the face. In order to determine whether there were differences in the perception of left and right sides of the face, real-life photographs were taken of 10 males and 10 females from both sides of their faces. The images were then shown as originals as well as mirror-reversed. Results indicated that regardless of the images being original or mirror-reversed, the left-side portraits were strongly preferred over the right-side; the left hemifaces elicited both higher aesthetic ratings and increased vertical pupil diameter. Vertical pupil diameter was linearly related to the pleasantness of the image regardless of whether the human models were male or female or whether the images were originals or mirror-reversed (Blackburn & Schirillo, 2012). These findings support the idea that the pupil dilation occurs when viewing pleasant images and pupil constriction occurs when viewing unpleasant images.

Rieger and Savin-Williams (2012) found that pupil area is a robust indicator of sexual orientation. Participants viewed thirty-second videos showing a neutral stimulus followed by a naked male or female engaging in a sexual activity. On a scale of 1-7, participants were asked to rate how sexually attractive they perceived the person, how sexually appealing they found the person, and how much they would like to date that person. Pupil area was computed as the number of the tracker's camera pixels occluded by the pupil. Results from the self-reported sexual orientation and the pupil data indicated the self-reported sexual orientation corresponded with pupil dilation to males and females. Specifically, bisexually-identified participants generally had substantial pupil dilation to stimuli of both sexes, whereas heterosexual males showed substantial dilation to stimuli of females compared to stimuli of males (Rieger & Savin-Williams, 2012). Their study shows that changes in the pupil area occur when a spectator experiences attraction to a stimulus. Both vertical pupil diameter and pupil area, which are measures of pupil dilation or constriction, can each be effective as objective measures of attractiveness (Rieger & Savin-Williams, 2012; Hess & Polt, 1960).

1.4.2 Luminance

In addition to emotional valence, pupillary responses occur automatically by either dilating or constricting the pupil in response to the changes in light intensity of the viewed scene (Laeng et al., 2012; Laeng & Endestad, 2011; Berman et al., 1996).

According to Laeng and Endestad (2011), pupillary responses to light reflect the perceived brightness or lightness of a visual illusion stimulus, not just the amount of physical light energy entering the eye. They used images of visual brightness illusions to see if peoples' pupillary responses reflected the physical luminance of the visual illusions or the perception of the visual illusions' luminance, where the two luminance levels did not match. They found that pupillary responses reflect the perceived brightness or lightness of a visual stimulus, not simply the physical amount of light reflected from a stimulus. Therefore, pupil area also indicates the subjective perception of light rather than the actual amount of light (Laeng & Endestad, 2011).

Berman et al. (1996) examined the relationship between horizontal pupil diameter and the text size acuity under two different luminance conditions: high and low luminance levels. Seven female and two male participants were asked to read words in Times-Roman font, of all different type-sizes, presented on 24 charts. Each participant read the words under two levels of surround luminance (indirect IL luminance of the room) and three levels of task luminance (direct luminance of task screen) (Berman et al., 1996). While reading these charts, eye-tracking software recorded participants' focus areas and horizontal pupil diameter. Results showed that an increase in task or surround luminance caused constriction of the pupils. Furthermore, smaller horizontal pupil diameters were found to improve visual performance regardless of task retinal illuminance or glare caused by the higher luminance of surround conditions (Berman et al., 1996).

As mentioned above, there are some individual characteristics that influence peoples' pupillary reactions (Watson & Yellott, 2012; Bergamin, Schoetzau, Sugimoto, & Zulauf, 1998). According to Bergamin et al. (1998), iris color is one of those differences. When comparing blue and brown eyes of 50 healthy volunteers, they found several differences between iris color and pupillary light reflexes. Iris color was found to significantly influence amplitude, contraction time, contraction velocity, and redilation velocity. Amplitude was measured as the difference between initial vertical pupil diameter and the vertical pupil diameter after pupillary light reflex. Contraction velocity is the pupil's rate of contraction (mm^2/s). Both amplitude and contraction velocity were greater in brown irides compared to blue irides. Similarly, redilation velocity (measured as the velocity of the pupil to dilate again after pupillary light reflex) and contraction time (measured as the time when the pupil contracts) were greater in brown irides compared to blue irides (Bergamin et al., 1998). However, iris color did not influence initial vertical pupil diameter, which was measured before the onset of the pupillary light reflex, or latency time, which was the time between the beginning of the stimulus presentation and the onset of pupillary light reflex. These findings suggest that iris color of the viewer also has an effect on the pupillary light reflex in normal healthy eyes.

1.4.3 Memory

Previous research has clearly indicated a significant relationship between pupil area and memory (Otero, Weekes, & Hutton, 2011; Kuchinke, Vo, Hofmann, & Jacobs, 2007; Otero, Weekes, & Hutton, 2006; Maw & Poplun, 2004). Otero et al. (2011) explored how pupil area changes during recognition memory. A remember/know procedure was utilized by asking participants to state whether they had remembered or knew a word that they may or may not have been previously shown in the study. In this study, pupil area was measured by an eye tracker and calculated as the number of camera pixels occluded by the pupil. Results indicated that pupil's dilated most when participants viewed items remembered from the study or seen prior to the study (old items) compared to items not previously shown during the study or known prior to the study (new items) during these recognition memory tests (Otero et al., 2011).

In a similar study, Maw and Poplun (2004) focused on how pupil area changed when viewing famous faces compared to non-famous faces. A temporary increase in pupil area was observed when viewing famous faces, which were known to participants, compared to non-famous faces, which were unknown to participants (Maw & Poplun, 2004). Additionally, Otero et al. (2006) conducted a study that presented participants with words or pictures during a learning phase, and found participants' pupil area increased more when viewing old items compared to new items.

Further confirming this idea that pupil area fluctuates with memory strength, Kuchinke et al. (2007) studied pupillary responses during lexical decision tasks, which required participants to judge whether a letter string was a word or not a word. Pupil data from the eye tracker indicated that in visual tasks, words that were less frequently seen evoked a stronger pupillary dilation compared to words that frequently appeared during a lexical decision task. Thus, results once again confirmed the dilation of pupils when short-term memory was activated (Kuchinke et al., 2007).

1.4.4 Cognitive Effort

From the 1960s on, there has been literature on the relationship between cognitive processes and pupil area, most of which focuses on the effects of cognitive effort (Granholm et al., 1997; Just & Carpenter, 1993; Hess & Polt, 1964). There is a considerable amount of evidence that suggests cognitive effort is associated with increased pupil area. Pupil area has been found to increase with arithmetic difficulty (Hess & Polt, 1964), sentence complexity during a comprehension task (Just & Carpenter, 1993), and also working memory load (Granholm et al., 1997).

Hess and Polt (1964) were the first to show that the size of pupillary response during mental activity is a function of how hard an individual has to work. They asked participants to do mental multiplication and as the level of difficulty gradually increased from 7 X 8 to 16 X 23, pupil size gradually increased. The increases in pupil size ranged from 4% to 30% of the vertical diameter from the period directly before the question was asked to the period directly before the question was answered, with vertical pupil diameter decreasing immediately after an answer to the question was given. Therefore, the pupillary response seems to reflect the information-processing load that is placed on the central nervous system by cognitive tasks. However, the sample size was too small (n=5) to claim any significant associations. There is also a greater margin of error, given pupil measurements were obtained, once again, from a Percepto-Scope and measured by hand using a millimeter ruler (Hess & Polt, 1964).

More recently, Just and Carpenter (1993) explored the intensity of cognitive processing during sentence comprehension by measuring pupillary response during reading tasks. Simple and complex sentences were presented separately to participants, while their pupil area and durations of focus areas were recorded using eye-tracking software (Iscan Model RK-426). The results indicated that more complex sentences increased horizontal pupil diameter; which they attributed to an increased intensity of mental processing. Similarly, Granholm et al. (1997) examined the relationship between pupillary responses and working memory. When giving participants a verbal working memory task that involved digital recall, horizontal pupil diameter was recorded by an infrared eye-tracking system (Micromeasurements System 1200). Results suggested horizontal pupil diameter increased with increased processing load, which was determined by the number of digits asked to recall. After what was considered overload (exceeding available cognitive resources), the pupil area started to decrease again. They concluded that horizontal pupil diameter increases with increased cognitive effort until cognitive overload, when the pupil diameter starts to decrease.

Although there is extensive research that pupil size is affected by mental activity and mental states, research on the relationship between pupil size and image attractiveness has been inconclusive to date. Given that positive emotions and pupil dilation have been found to occur simultaneously, then images that have been rated as attractive should increase pupil dilation; however, prior research looking specifically at positive ratings and pupil dilation has only been conducted with sexually arousing stimuli. Thus, further investigation of pupillary responses is necessary to evaluate a broader scope of whether pupil dilation is an automatic response to the perceived attractiveness of all images, not just sexually arousing images.

1.5 Eye Movement Tracking Technology

Eye movement tracking technology provides an objective way of measuring the impact of a visual image. Researchers have found eye movement tracking is useful in determining how users view, search, and process a visual image and enables the capturing of pupil area measurements (Andreassi, 2007; Cowen, Ball, & Delin, 2002).

An infrared light source is used to illuminate the eye, which creates highly detectable reflections from the cornea and in the pupil that can be detected by IR cameras. The cornea and the pupil absorb visible light but reflect infrared light better than the rest of the body, and these reflections can be detected and used to indicate the direction of gaze (Nielsen & Pernice, 2010). When an IR LED light is reflected in the human eye the reflection from the cornea makes a bright spot, known as the glint, in an image of the eye. This reflection serves as a reference point for which we are able to calculate the center of the pupil and cornea center. Gaze direction can be calculated using the relative position between the glint that is made by reflection of the light and a center of the iris in the image (Yoo, Kim, Lee, & Chung, 2002). These two points enable the computation of a vector to yield intersections against regions of interest, which gives an x,y coordinate intersection on the screen (Nielsen & Pernice, 2010). For example, if the user saw the IR LED directly, then the glint would be near the center of the iris; on the other hand, the farther the eye's fixation is from the IR LED, the longer the distance between the glint and the center of the iris (Yoo et al., 2002).

In the early 1900s, when eye tracking technology was first developed, eye tracking devices were invasive and did not provide very accurate measurements (Pavlas, Lum, & Salas, 2010). Some of the earlier devices required participants to strap on a helmet with goggles, to put on contact lenses with a hole for the pupil, or to attach electrodes around the eyes (Andreassi, 2007). Today, eye tracking devices include standalone infrared cameras that can be positioned beneath a standalone computer screen. Additionally, the physical tracking of eye movements and the data recording capabilities of today's eye tracking devices are faster and more accurate than previous tools. The ability to accurately capture measurements of eye movements, pupil area, areas of focus, and other characteristics of one or both eyes while a user is engaging in a given task allows researchers to observe exactly subconscious reactions to an image displayed on a screen (Nielsen & Pernice, 2010; Rayner, 1998).

There are several ways to analyze data collected from an eye tracking system. Software processes the raw data of fixation points and saccades, to provide different visual displays that summarize the data. Two ways of looking at eye tracking data are heatmaps and lookzones.

1.5.1 Heatmaps

According to Nielsen and Pernice (2010), heatmaps are the best-known visualization technique for eye tracking studies. In a heatmap, a screenshot of the interface is taken and color-coded according to the number of times a person viewed an area and the duration of focus on those areas (Nielsen & Pernice, 2010). Heatmaps can represent either the number of fixations or the duration of fixations depending on the setting chosen by the analyst. They give a quick summary of what areas participants were focusing on and what they were ignoring. Heat maps can be relative, because researchers can change the duration of gaze time that defines a fixation, giving a different number of fixations or fixation durations, and different heatmaps. Color settings can also be altered to generate heatmaps of different intensities in order to concentrate on specific areas. These settings may be altered in order to allow researchers to concentrate on specific areas and control the number and/or duration of fixations. Figure 1.6.1 below shows an example of a heatmap of a website with text from Nielsen and Pernice's study (2010). In this figure, the areas of red are the areas where a participant spent the most time viewing, yellow areas are where a participant spent less time viewing, blue areas are where a participant spent even less time viewing, and gray areas are where participants did not even focus on.

Figure 1.5.1: Heatmap of website (Nielsen & Pernice, 2010)

1.5.2 Lookzones

Lookzones are regions of interest that are determined by the analyst. Lookzones may be any size or shape. There is no limit to the number of lookzones that can be made on a single image. Lookzones are created to provide statistics about regions of interest on the image presented. Once specific lookzones are created, statistics of how long a participant spent viewing the lookzone area in percentages of time or by number of seconds. Figure 1.6.3 shows an example of lookzones created on an image of the Amazon website (Pan et al., 2004). In the image, each area enclosed in a black box is a different lookzone that has been created by the researchers in order to determine the specific percentage of time spent looking at that area. For example, the "amazon.com" logo, which is highlighted in yellow, has been created as a lookzone to determine how much time participants spent looking specifically at the logo (See Figure 1.6.3. below).

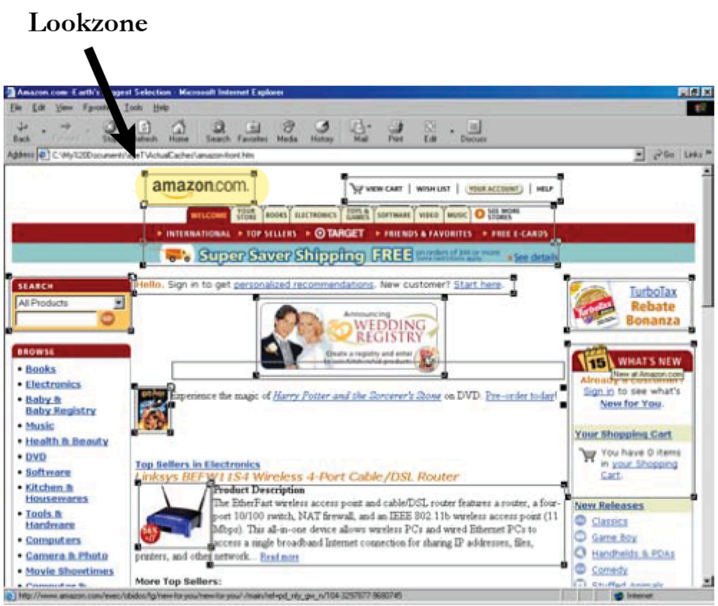

Figure 1.5.2: Lookzones on Amazon website (Pan et al., 2004)

1.6 Complexity

Research suggests visual complexity depends on the objects, textures, and colors in a scene, all of which can all be arranged in a variety of spatial layouts to form a visual image (Olivia et al., 2004; Rayner, 1998). According to Heylighen (1997), the perception of complexity is correlated with the variety in the visual stimulus, which can be altered in two ways. First, the perceived visual complexity can increase when the background remains constant but the number of objects increases. Second, perceived visual complexity can increase with an increasing dissimilarity of objects or variety of materials, while the number of objects itself remains constant (Heylighen, 1997). Furthermore, Olivia et al. (2004) found that visual complexity, measured as a rating of perceived complexity of an image, depends on the viewer's ability, the amount of grouping of objects or areas, the quality of perceived parts within the scene, familiarity with the scene, and existing knowledge of objects within the scene.

Thus, when a human model is added to a visual image, the image complexity increases from simple to moderately complex (Geissler et al., 2006; Olivia et al., 2004; Berlyne et al., 1968). The level of complexity can greatly influence a viewer's first impression and the attractiveness rating of a visual image (Tuch et al., 2009; Olivia et al., 2004; Berlyne et al., 1968). A moderately complex visual image has been found to elicit a more positive first impression and a higher attractiveness rating compared to either a simple or an overly complex visual image (Tuch et al., 2009; Berlyne, 1974). Prior research indicates moderately complex images elicit longer viewing times and increased perceived image attractiveness; while simple stimuli are rated boring and overly complex stimuli are rated confusing, and both elicit shorter viewing times (Nielsen & Pernice, 2010). It is possible that the increase in image complexity with the addition of a human model might foster a more positive first impression, entice the viewer to process the image more thoroughly, and judge it to be more attractive (Bradley, Houbova, Miccoli, Costa, & Lang, 2011; Tuch et al., 2009; Giessler et al., 2006; Olivia et al., 2004; Berlyne, 1974).

1.6.1 Simple vs. Complex Images

Previous research has found that fixations are associated with cognitive processing and forming a perception of a visual stimulus (Cutrell & Guan, 2007; Pan et al., 2004; Petersen & Nielsen, 2002; Viviani, 1998). During saccades, when the eye is not focusing on a specific area and visual information is not being perceived, the stimulus is merely being scanned without the brain retaining any visual information (Viviani, 1998). Previous research has indicated that fixation frequency is dependent on the degree of importance, while fixation duration is dependent on the complexity and difficulty of a visual display (Buscher et al., 2009; Pan et al., 2004; Rayner, 1998). More specifically, a greater number of and/or longer fixations have been associated with increased detail and complex images, while fewer and/or shorter fixations have been associated with simple images (Bradley et al., 2011; Guo, Mahmoodi, Robertson, & Young, 2006; Weizmann, 1979; Wolf, 1970).

A study by Weizmann (1979) looked specifically at the effect of complexity on infant attention. In this study, forty-one 8-, 10-, and 12-week-old infants viewed three stimuli differing in complexity. Results indicated infants fixated for longer periods of time on more complex stimuli compared to simple stimuli. Additionally, males and females differed in fixation duration over time; specifically, overall fixation times declined with age for males but not for females (Weizmann, 1979).

Wolf (1970) found that increased complexity led to an increase in the number of fixations, but only to a point. In this study, subjects from grades 6, 8 and 11 were asked to view four 19-minute motion picture films (Wolf, 1970). During the viewing, areas of focus on the screen were analyzed, but fixation durations were not. A density analysis showed that subjects looked at few well-defined areas of the screen. As the visual complexity increased, the number of areas of focus increased until the visual image became too difficult for the subject to comprehend. When the stimulus became extremely complex, the subjects tended to avoid the stimulus or to focus centrally on the screen (Wolf, 1970). Although these results were based on a film, rather than a static image, they provide evidence that with increased complexity, the number of areas of focus (fixations) increase, but only to the point of overload.

Bradley et al. (2011) further explored the relationship between complexity and eye movements. More specifically, they compared eye movements of 24 college students while viewing 192 images that were either simple figure-ground compositions or complex scenes, which included multiple objects and a varied background. Results indicated a significant effect of complexity on the number of fixations: images of complex scenes were found to provoke more fixations and a broader scanning of the visual image array compared to simple figure-ground compositions.

Nielsen and Pernice (2010) examined the relationship between complexity and eye movement patterns, but found different results from research described above (Bradley et al., 2011; Weizmann, 1979; Wolf, 1970). Their study explored whether there were a greater number of fixations on objects against a simple versus a crowded background, and whether more attention was paid to single or multiple objects. Results showed that objects with simple backgrounds received more attention from users. When looking at a website, 28% of participants focused on objects in a simple setting or a simple background; however, only 14% of participants focused on objects with a crowded background or busy setting. In the same study, participants looked at websites with either single or multiple objects on them. Results showed that single objects received more attention: 26% of participants focused on a single object, while only 20% of participants focused on multiple objects. Similarly, 20% of users looked at images with a single person, while only 17% of users looked at images with two or more people. These findings further indicate the presence of a single person in an image increases focus and prompts more fixations compared to images with multiple people (Nielsen & Pernice, 2010).

Faces prompt fixations because they provide visual information about an individual's gender, age, and familiarity; facial expressions offer cues to the individual's state of mind (Guo et al., 2006). In their study, the eye movements (measured using CED1401) of three male adult rhesus monkeys were recorded while the monkeys viewed four types of images: neutral monkey face images, natural scene images, familiar natural scene images taken from the monkeys' daily environment, and scrambled images of monkey faces. Results indicated a similar number of fixations on face images and natural scene images; however, fixation duration was longer on face images compared to natural scene images. Additionally, fixation durations decreased when face images were scrambled. The extended fixation duration on faces was hypothesized to be due to the increased detail of facial features.

Barton, Radcliffe, Cherkasova, Edelman, and Intriligator (2006) also explored fixations while viewing images of human faces. In their study, 8 human participants viewed images of either famous or novel faces that were upright or inverted. Inverted images were more difficult to recognize and required more cognitive effort. Results indicated fewer fixations when participants viewed images of famous faces compared to images of novel faces. Additionally, the number of fixations on inverted novel images was significantly higher than the number of fixations on upright novel images. However, there was no difference in the duration of fixations for either images of famous faces compared to images of novel faces or upright images compared to inverted images (Barton et al., 2006).

In summary, there appears to be evidence that more fixations will occur in the more informative areas of an image; and different types of images will prompt different fixation behaviors. From an abundance of eye tracking studies, it is clear that eye movements are driven by properties of the visual environment and by cognitive processes (Tuch et al., 2009; Barton et al., 2006; Geissler et al., 2006; Berlyne, 1974; Berlyne et al., 1968); however, it is still unclear how image complexity effects the eye movement patterns and areas of focus when viewing a product with or without a human model present.

1.7 Male vs. Female Differences

Prior research has found that gender influences fixation frequency and duration when viewing human faces (Rennels & Cummings, 2013; Nummenmaa, Hietanen, Santtila, & Hyona, 2012). In Rennels and Cummings' (2013) study, male and female participants viewed faces of male and female human models, who posed with neutral expressions. Results showed adult females made more, shorter fixations compared to adult males. (Rennels & Cummings, 2013). Furthermore, Nummenmaa et al. (2012) found the gender of the human model present in a stimulus influences male and female fixation durations. More specifically, males were found to fixate on female models longer than females, while females fixated longer on male models. These findings indicate the content of the stimuli impacts male and female fixations (Nummenmaa et al., 2012).

Extending beyond stimuli of human faces, the gender differences in fixations are inconclusive (Andersen, Dahmani, Konishi, & Bohbot, 2012; Pan et al., 2004; Miyahira, Morita, Yamaguchi, Morita & Maeda, 2000). In one eye tracking study by

Pan et al. (2004), male and female participants viewed 22 popular webpages. Female participants had significantly shorter mean fixation durations compared to males; however, males and females did not differ significantly in fixation times or saccade rates (Pan et al., 2004). This suggests gender does have an effect on viewing patterns.

More recently, Andersen et al. (2012) found gender differences in viewing patterns for seven participants who were asked to navigate a virtual maze. Results indicated that females took longer to complete the virtual maze and made more errors compared to men. Additionally, females had a significantly greater number of fixations and longer fixations compared to men. However, the sample size was small (n=7), so while suggesting the influence of gender on eye movement, this needs to be further studied, considering that Andersen and colleagues' (2012) results suggested the opposite effect of gender on fixation duration compared to Pan and colleagues' (2004) results.

Additionally, Miyahira and colleagues (2000) found the opposite effect of gender differences on the number of fixations from findings of Andersen et al.'s (2012) study. In this study, participants were asked to view simple black and white geometric shapes. Results indicated males elicited a greater number of fixations compared to females (Miyahira et al., 2000). Given that there have been studies indicating opposite effects on gender differences in fixation duration and the number of fixations while viewing stimuli without human faces (Andersen et al., 2012;

Miyahira et al., 2000; Pan et al., 2004), the effect of gender these eye movement patterns needs to be further assessed.

1.8 Designer vs. Non-Designer Differences

In 1993, Nodine, Locher, and Krupinski studied how artists and non-artists differ in their viewing patterns for paintings. Each participant viewed six pairs (original and slightly altered) of paintings for twelve-second viewing periods per pair, while an eye tracking system captured eye positions (Nodine et al., 1993). Eye movement data suggested non-artists focused more on individual objects and had fewer but longer fixations, while trained artists focused on the relationship among compositional elements (lines, colors, shapes, space) and had a greater number of shorter fixations. However only descriptive eye-movement findings reported, and no statistical analysis was conducted. Furthermore, the paintings used in the study were famous, so the paintings were well known to the group of artists, but not to the non-artist group, which may have influenced eye movements (Nodine et al., 1993). As mentioned above, recognition of an object in a visual image increases pupil size (Maw & Poplun, 2004). Additionally, recognition has been found to decrease the number of fixations and reduce scanning duration (Barton et al., 2006). Given the impact of recognition and memory, it is possible that these famous paintings were a confounding variable on eye movements for artists who had recognized the stimuli. Although this study does not provide significant evidence and may have had confounding variables, the observed eye movements suggested a difference between artists and non-artists.

Vogt and Magnussen (2007) were intrigued by Nodine et al.'s (1993) study, and further explored the difference between artists and non-artists eye movements. Trained artists and non-artistic psychologists were asked to free scan 16 images and then asked to remember the 16 images, while an eye tracking system captured fixations, gaze trails, and saccades. When viewing and memorizing the images, non-artists spent significantly more time looking at main objects or elements in the image, while artists were more scattered in their viewing patterns. A verbal test of memory recall showed no overall difference in the number of images remembered, but artists remembered more details from the images compared to non-artists. Results indicated non-artists had fewer, longer fixations with repeated viewing, while trained artists had more, shorter fixations with repeated viewing.

Although both Nodine et al.'s (1993) study and Vogt and Magnussen's (2007) study indicated artistic backgrounds influence eye movement patterns, further exploration is required to validate the relationship in order to understand systematic eye movement differences amongst those with and those without artistic backgrounds.

1.9 Summary of Proposed Research

This study further investigates whether increased image complexity through the presence of a human model and the attractiveness of a human model influences the perceived attractiveness of an image of an ergonomic product. It also investigates whether pupillometry can be used as an objective measure of overall perceived image attractiveness. Furthermore, this study explores how the increased in image complexity resulting from adding a human model systematically affects eye movement patterns in terms of number of fixations, duration of fixations, and location of fixations on visual stimuli. Finally, it will compare differences, if any, between male and female participants and between designers and non-designers.

A better understanding of how image complexity through the use of a human model and how the attractiveness of a human model influences perceived attractiveness, how pupil area responds to any changes in attractiveness, and how eye movements are affected by image complexity will be useful in the design and marketing worlds, where ergonomic products are expected to be displayed in the most flattering way. Additionally, knowing gender or designer status differences will allow designers and advertisers to promote ergonomics products in a way that captures more attention and appeals to a targeted clientele.

1.10 Research Hypotheses

Based on the literature that has been reviewed, eight hypotheses were developed and tested in this study. The first two hypotheses were formed based off of prior studies that have tested the impact of an attractive human model on advertisements and the impact of image complexity on self-reported judgments of images. Given that a human model attract viewers (Nielsen & Pernice, 2010), that an attractive human model increases product sales (Caballero & Pride, 1984; Dion et al., 1972) and promote positive attitudes (Nielsen & Pernice, 2010), that the addition of a human model to an image alongside a product moderately increases the complexity of an image (Tuch et al., 2009; Olivia et al., 2004), and that moderately complex images elicit the most positive aesthetic judgment from viewers (Tuch et al., 2009; Geissler et al., 2006; Berlyne, 1974), the image complexity and the attractiveness of a human model in an image may affect overall image attractiveness ratings.

Hypothesis 1: Moderately complex images will receive higher perceived attractiveness ratings compared to simple images.

Hypothesis 2: The higher the perceived attractiveness rating of the human model, the greater the difference between the attractiveness ratings of the moderately complex image and the simple image.

The third and fourth hypotheses were formed off of prior pupillary response studies, which have found pupils dilate with increased interest (Rieger & Savin-Williams, 2012; Hess & Polt, 1960) and cognitive effort (Granholm et al., 1997; Just & Carpenter, 1993; Hess & Polt, 1964). Although prior research has utilized stimuli of naked human models to explore the effect of interest on pupillary responses, there is no clear relationship between interest and pupil dilation when viewing stimuli of fully clothed human models. The factor of attractiveness of a fully clothed human model in an image may affect pupillary responses.

Additionally, the presence of a human model used to increase cognitive effort, and thus, increase pupil dilation has not yet been tested. Given that an increase in complexity is an increase in cognitive effort (Olivia et al., 2004) and that increased cognitive effort affects pupillary responses (Granholm et al., 1997; Just & Carpenter, 1993; Hess & Polt, 1964), it has been hypothesized that the presence of a human model used to increase complexity may also affect pupillary responses.

Hypothesis 3: Pupil dilation will increase as the perceived image attractiveness increases and as the perceived model attractiveness increases.

Hypothesis 4: Pupil constriction will occur when viewing simple images and dilation will occur when viewing moderately complex images.

The fifth hypothesis was formed from prior research that studied the relationship between eye movements and image complexity (Bradley et al., 2011; Buscher et al., 2009; Cutrell & Guan, 2007; Guo et al., 2006; Pan et al., 2004; Petersen & Nielsen, 2002; Viviani, 1998; Weizmann, 1979; Wolf, 1970). The number of fixations has been found to increase with the degree of importance, while the fixation duration is dependent on the complexity and difficulty of a visual display (Buscher et al., 2009; Pan et al., 2004; Rayner, 1998). It is hypothesized that an increase in the complexity through the presence of a human model will increase the number of fixations and decrease fixation duration.

Hypothesis 5: Increased image complexity will increase the number of fixation points and decrease average fixation durations.

The human model has been found to capture attention (Nielsen & Pernice, 2010). Specifically, human faces have been found to prompt areas of focus and longer fixation durations (Guo et al., 2006). However, it is still unclear how the presence of a human model will affect focus areas. Given the evidence that human faces are informative areas that draw attention from users (Tuch et al., 2009; Barton et al., 2006; Geissler et al., 2006; Berlyne, 1974; Berlyne et al., 1968), it is hypothesized that the presence of a human model will attract the most attention.

Hypothesis 6: The presence of a human model will attract more attention than the object alone.

Research has shown that differences in viewing patterns exist between males and females (Rennels & Cummings, 2013; Andersen et al., 2012; Nummenmaa et al., 2012; Pan et al.; 2004; Miyahira et al., 2000). The difference is clear that females make more, shorter fixations compared to males when viewing images of human faces (Rennels & Cummings, 2013; Nummenmaa et al., 2012); however, extending beyond images of human faces, the gender differences in viewing patterns are inconclusive (Andersen et al., 2012; Miyahira et al., 2000; Pan et al., 2004). Stimuli content may impact gender differences in viewing patterns. Based off of prior research findings of gender viewing pattern differences the following hypothesis was generated.

Hypothesis 7: Males will have fewer fixations, longer fixation durations, and different areas of focus compared to females.

Prior research has identified a difference in artists' and non-artists' viewing patterns (Vogt & Magnussen, 2007; Nodine et al., 1993). Specifically, non-artists had fewer, longer fixations, while artists had more, shorter fixations (Vogt & Magnussen, 2007). Additionally, non-artists focused centrally on an image, while artists focused on multiple areas throughout an image (Nodine et al., 1993). Although prior research may have had confounding variables on eye movement measures, there appears to be a difference in viewing patterns between people with artistic training and people without, which has formed the following hypothesis.

Hypothesis 8: Designers will have more fixations, shorter fixation durations, and different areas of focus compared to non-designers.

CHAPTER 2: METHODS

2.1 Apparatus

2.1.1 Chairs

A total of 32 images of 16 different chairs and 8 different female models were used. The 16 chairs photographed as stimuli were comprised of 6 ergonomic office chairs and 10 designer leisure chairs. The selection of the 16 chairs was based on chair height, lack of patterns, and availability of chair. All of the 16 chairs had similar height and had solid colors, which provided a simple visual aesthetic. The 16 chairs were stationed at the same location for photography within Martha Van Rensselear Hall and the Human Ecology Building at Cornell University. Table 1.1.1. in Appendix B lists the chairs.

2.1.2 Human Models

Eight females sitting in the Cornell Human Ecology Commons, a large atrium connecting the Human Ecology Building to Martha Van Rensselear Hall, were chosen for their dark color pants, their closeness to the camera and chairs set-up, and their willingness to participate as a human model for this study. All of the human models were aged between 19 and 22 years old. Each female model was wearing black or navy pants and asked to put on a black overcoat provided at the camera and chairs station in order to eliminate any possible confounding effect of clothing color differences between stimuli. Human models were asked not move the chair from its original angle, which was at a 45° angle to the camera, and to turn their head to face the camera and to present a neutral face when the picture was taken.

2.1.3. Stimuli

The stimuli consisted of 2 screen images for each of the 16 chairs, one of the chair against a white background and one of the chair in the same location against the same white background with a person sitting in the chair in a three-quarters pose looking directly at the camera, which has previously been found to increase attraction (Nielsen & Pernice, 2010). All images were photographed using a digital camera (Nikon D3000) on a stationary tripod. Images were all photographed in the same location within the same hour, therefore keeping lighting and image angle consistent.

2.1.4 Eye Tracking System

Data was collected using a remote infrared (IR) eye tracking system (FaceLAB 4.5). This system consists of two small IR video cameras that were positioned beneath a free-standing liquid crystal display (LCD) computer screen (20" Dell), on which visual stimuli were presented for each participant to view. IR sources are mounted either side of the LCD screen and below the LCD screen to provide the reflected IR light targets for tracking. These IR cameras are high resolution with a frame rate of 60-Hertz, and optically detect the position of the eyes from IR reflections, which come from the sclera without the participant having to wear any apparatus. Data consists of fixation points, fixation duration, saccade duration, pupil diameter (horizontal and vertical), pupil area, and eye blinks. Fixation duration is measured in milliseconds, pupil diameters are measured in millimeters times 10, and pupil area is measured in millimeters squared times 100. Data was post-processed using the eye tracking software (GazeTracker v9.0), which calculated average fixation time, average number of fixations, average pupil area, percentage of time viewing a specific area, and additionally, creates visuals of where participants look.

2.1.5 Luminance Contrast Meter

A Brüel and Kjaer luminance contrast meter (Type 1100) was used to determine the luminance of each stimulus on the computer screen. In the central zero degree sitting position, the lens of the photometer was aimed at the center of the screen image was and positioned approximately 63 centimeters from the screen (see Figure 2.1.1 below). This measured the luminance of a 14.14 cm^2 area the screen, which covered most of the image, but did not include the white background area around the image. The white background area was measured separately and had a constant luminance of 195 cd/m^2, while the center stimulus luminance values ranged from 9.9 cd/m^2 to 73 cd/m^2 (See Figure 1.1.1. in Appendix A).

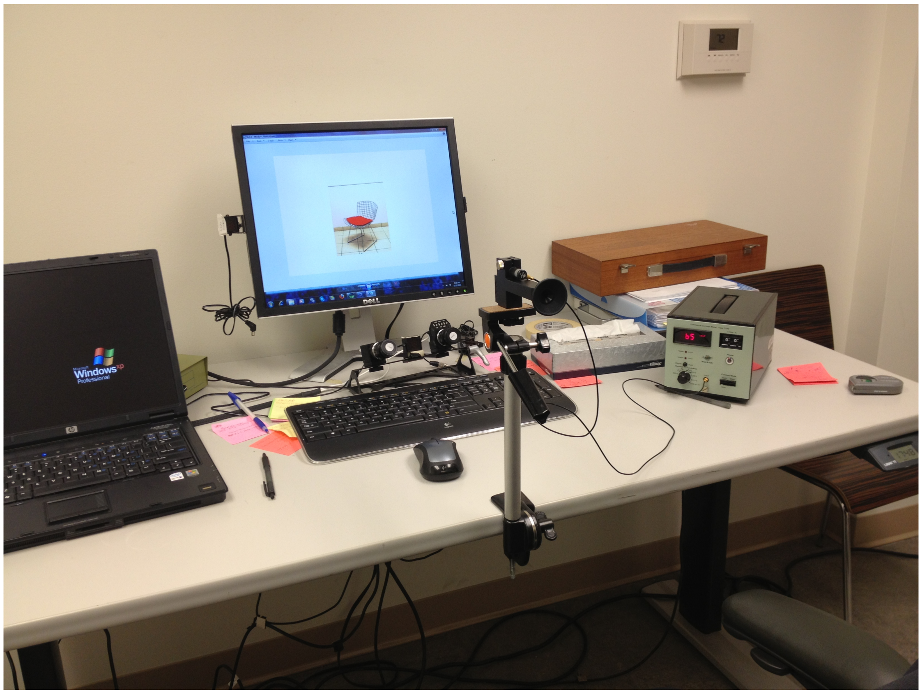

Figure 2.1.1: Luminance contrast meter and eye tracking apparatus

2.2 Participants

Subjects (N=32) were recruited through SUSAN, a site created for Cornell University's Department of Psychology to allow students to sign up for available studies to receive money or extra credit points in a course currently enrolled in. In this study, students were offered either $25 or 1 extra credit point for their participation. Out of the 32 total participants, 16 students were male and 16 students were female (50% of each gender). Of the 16 females, 8 were classified as designers and 8 were classified as non-designers. Similarly, of the 16 males, 8 were classified as designers and 8 were classified as non-designers. These classifications were based on each participant's degree major. Ages ranged from 18 to 25 with a mean age of 20.5 years. None of the participants wore glasses, although 6 participants wore contacts to correct their vision. None of the participants were cigarette smokers. Of the 32 participants, 1 male was bisexual, 3 males were homosexual, and 28 male and female participants were heterosexual. Sexual orientation is of importance because heterosexuals and homosexuals have been found to rate men and female differently (Jankowaik, Hill & Donovan, 1992). Specifically, heterosexual males rate female models higher than homosexual males (Jankowaik et al., 1992), and heterosexual females rate female models higher than homosexual females (Nash, Fieldman, & Hussey, 2005). All of the participants had normal color vision. Participants were from various cultural backgrounds and were all enrolled as full-time students at Cornell University.

2.3 Measures

2.3.1 Designer Status

Each participant was asked to declare his or her area of focus (academic major) in order to categorize the participants into designer/non-designer groups. A participant was labeled a designer if his or her major was Art, Architecture, Interior Design, or Graphic Design. Participants outside of these art-related majors, such as Economics, Psychology, Biology, or Engineering, were categorized as non-designers. Participants were grouped into one of these two designer/non-designer categories in order to compare the two groups and determine if there were any differences in eye-movement patterns or attractiveness ratings.

2.3.2 Attractiveness Ratings

Each participant verbally gave an "overall attractiveness of the image" rating for each of the 32 stimuli and each of the 8 human models' headshots. The overall attractiveness rating scale was from 1 (very unattractive) to 10 (very attractive). The participants were given 2 seconds to rate the overall attractiveness of each image. The time period was deliberately short to ensure participants gave the rating derived from their initial thought.

2.3.3 Pupil Area

Eye tracking analysis software (GazeTracker v19) was used to measure the vertical pupil diameter of the left eye, the vertical pupil diameter of the right eye, and calculate the average pupil area from both eyes combined along with their corresponding standard deviations for each participant for each stimulus. Vertical pupil diameter was measured top to bottom of each the left and right eye 66 times per second. The software calculated average pupil area by adding the sum of all left pupil diameters divided by 2 and the sum of all right pupil diameters divided by 2 and then multiplying that summed number by pi (π). The units for pupil diameter of each eye were millimeters times 10, and the units for average pupil area of both eyes were millimeters squared times 100. The change of pupil area as a response to a stimulus was equal to the average pupil area while viewing a stimulus minus average pupil area while viewing the preceding white image.

2.3.4 Number of Fixations and Fixation Duration

Eye-tracking software (GazeTracker v9.0) calculated the number of fixation points and the average duration of fixation points for each participant for each stimulus.

2.3.5 Complexity

Stimuli were categorized as either simple or moderately complex based on the absence/presence of the human model.

2.3.6 Heatmaps

Heatmaps were generated by the eye tracking software (GazeTracker v9.0 and FaceLAB 4.5), and used to represent the areas of the stimuli where participants were focusing. Heatmaps were constructed based off of the number of fixations a user spent on an image. The render radius and strength determine different intensities within a heatmap. The default settings (render radius and strength are 25 and 96 respectively) were used for this study. A composite heatmap of each stimulus was generated for the combined participants in each gender and each designer status group.

2.3.7 Lookzones

Lookzones were created for each of the 16 moderately complex images. Two lookzones were created per stimulus: one for the human model's face and one for the chair. The eye tracking software (GazeTracker v9.0 and FaceLAB 4.5) calculated the percentage of time each of the 4 groups (female/male and designer/non-designer) spent looking at a specific area (lookzone) on the stimulus.

2.4 Procedure

All participants were individually tested in the windowless Cornell Human Computer Interaction Usability Laboratory. Upon arrival to the Laboratory, each participant was welcomed, asked to sign a written consent form, and asked if he or she had any questions before beginning. For the eye-tracking portion of the study, each participant was asked to take a seat centered with the LCD screen, which display the stimuli. After the participant was comfortably seated, the height of the electric height-adjustable table (Workrite) was adjusted to the height of the seated participant in order optimize camera position with respect to both eyes. Following the table height adjustment, the cameras were focused and gaze was calibrated for each participant. Gaze was calibrated by having the participant focus on each of the nine-equispaced blinking dots on the computer screen (3 X 3). If needed, the calibration process was repeated until the system was accurately calibrated to the participant's eye. Then, each participant began the 30-minute experimental session, in which they viewed a total of 40 images (32 images with chairs, 8 images of human model headshots). For each slide, participants were asked to verbally rate the attractiveness of the image on a scale from 1 (not attractive) to 10 (very attractive). Each image was presented for 2 seconds before switching to a white screen. The white screen was shown for 2 seconds before and after each image for 2 seconds in order to stabilize pupil area with a standard pre- stimulus luminance. After the participant viewed all 32 simple and moderately complex images, the participant was asked to verbally rate the attractiveness of each of the 8 female models as the human model headshots were sequentially presented on the screen for 2 second periods. This rating was also on a 1 (not attractive) to 10 (very attractive) scale. The order of the stimuli were randomized by the eye tracking software and fixed to be the same randomized sequence for each participant.

During the participants viewing of each of the 32 simple and moderately complex stimuli, the eye tracking system recorded the participant's time, fixation points, pupil vertical diameter, saccades, and gaze trail, which were later statistically analyzed. This research procedure was reviewed and approved by Cornell University's Institutional Review Board for Human Participants.

2.5 Data Analysis

Image attractiveness ratings and average pupil area, number of fixation points, and average fixation duration for each stimulus for each participant were inputted into an Excel file and imported to a multivariate statistical package (SPSS v19) for analysis.

To test whether the difference between the attractiveness rating of the moderately complex image minus the attractiveness rating of the simple image increases with higher perceived attractiveness of the human model, a mixed model analysis of variance was run. The difference of image attractiveness was calculated as the attractiveness rating of the moderately complex image – attractiveness rating of simple image with the paired chair.

The distribution of average pupil area, overall image attractiveness ratings, model attractiveness ratings, number of fixations, and average fixation time were analyzed separately to detect any outliers or non-normal data. For each variable, a histogram was graphed and kurtosis and skewness values were calculated to determine whether the data was approximately normally distributed. Skewness measures Normality, a skewness value of 0 is perfectly normal, and a skewness value of less than 2 is assumed approximately normal (Curran, West, & Finch, 1996). Kurtosis is a measure of the spread of the distribution relative to a normal distribution. A kurtosis level of 3 is perfectly normal, and a kurtosis level less than less than 7 can be assumed approximately normal (Curran et al., 1996). Non-normal data were cleaned of outliers and transformed in various ways depending on the variable prior to statistical analysis in order to make the data appear to more closely meet the assumptions and improve the interpretability. The distribution of the change in average pupil area from the white image to the stimulus was skewed. Data points were made positive through the addition of 1236 (the highest negative number) to each point, deleting any points beyond three standard deviations from the mean, then 1236 was subtracted from all data points to revert back to original mean value. Seven outliers were deleted from the data. The deleted data points were much too large of a dilation or constriction to be anything but a squint or a blink (See Figure 3.1.1. in Appendix A). For the change in average pupil area data without the outliers the kurtosis value was 3.581 and the skewness value was equal to 0.323 (See Table 2.1.1. in Appendix B). Given that these transformed values have a skewness level below 2 and kurtosis level below 7, the values indicate the data was approximately normally distributed.

The distribution of overall image attractiveness ratings was approximately normal (See Figure 3.1.2. in Appendix A). There did not appear to be any outliers. The kurtosis value was -0.913 and the skewness value was 0.144 (See Table 2.1.1. in Appendix B), which indicate the data is approximately normally distributed. Similarly, the distribution of model attractiveness ratings appeared to be approximately normally distributed with no outliers present (See Figure 3.1.3. in Appendix A). For model attractiveness ratings, the kurtosis value was -0.864 and the skewness value was -0.056 (See Table 2.1.1. in Appendix B), which both indicate normality.

The distribution of the number of fixation points was approximately normal with one outlier, which was deleted from the data (See Figure 3.1.4. in Appendix A). For the number of fixation distribution, the kurtosis value was -0.386 and the skewness value was equal to -0.061 (See Table 2.1.1. in Appendix B). These values suggest the data is approximately normally distributed.

The distribution of the average fixation time was skewed. There appeared to be an outlier that was very small and 10 that were very large. Any data point that was longer than a second was considered an outlier since that indicated a participant was fixating on a single point for more than half of the viewing time. The average fixation time data was transformed by the natural log to normalize the data. The distribution of the natural log average fixation time appeared to be approximately normal (See Figure 3.1.5. in Appendix A). For the distribution of log average fixation time, the kurtosis value was 2.24 and skewness value was equal to 1.207 (See Table 2.1.1. in Appendix B). These skewness and kurtosis values suggest the log average fixation time data was approximately normally distributed. Thus, log average fixation time was used for statistical analysis.

Subsequent analyses used a mixed model analysis of variance for the transformed data. The significance level was set at $p \leq 0.05$.

CHAPTER 3: RESULTS

The results of the statistical analysis are presented in the following sections.

3.1 Image Complexity and Image Attractiveness

A mixed model analysis of variance was run to test the first hypothesis, which predicted moderately complex images would receive higher attractiveness ratings than simple images. In the mixed model analysis of variance, overall image attractiveness tested image complexity, gender and designer status as fixed effects, with participant ID and chair as random effects. Inter-individual variability accounted for 12% of the total variance for overall image attractiveness ratings and 88% was residual variability among participants perceived attractiveness ratings (See Table 3.1.1. in Appendix B). There was a significant main effect of image complexity on overall image attractiveness ($F(1,989)=21.077$, $p=0.000$): moderately complex images received higher perceived attractiveness ratings (4.992) compared to simple images (4.385) (See Tables 3.2.1. and 3.2.2 in Appendix B), which confirms the hypothesis. No other main effects or interactions were statistically significant.

3.2 Image Attractiveness and Model Attractiveness

To test the second hypothesis, which predicted the difference between attractiveness ratings of the simple image and the moderately complex image of the same chair would increase as the human model attractiveness rating increased, a mixed model analysis of variance was run. The mixed model analysis of variance for the difference in image attractiveness tested human model attractiveness, gender, and designer status as fixed effects, with participant ID and chair as random effects. Of the total variance for image attractiveness ratings, inter-individual variability accounted for 10%, chair-to-chair variability accounted for 13%, and 77% was residual variability (See Table 4.1.1 in Appendix B). There was a significant main effect of model attractiveness ratings on the difference in overall image attractiveness ratings ($F(9,465)=4.34$, $p=0.000$) (Table 4.3.1. in Appendix B): as model attractiveness ratings increased, the difference in image attractiveness ratings between the moderately complex image and the simple image increased (See Table 4.3.2 in Appendix B). No other main effects or interactions were statistically significant.

3.3 Image Attractiveness and Pupil Area Change

A mixed model analysis of variance was run to test the first part of the third hypothesis, which predicted pupil area increases as the perceived overall image attractiveness increases. The mixed model analysis of variance for average pupil area change tested image attractiveness, gender, and designer status as fixed effects, and participant ID as a random effect. Inter-individual variability was not a significant percentage of the total variance for change in average pupil area (See Table 5.1.1. in Appendix B). There was no significant main effect of overall image attractiveness (See Tables 5.2.1. and 5.2.2. in Appendix B). Additionally, no other main effects or interactions were statistically significant.

3.4 Pupil Area Change and Stimulus Luminance

Given that the results did not confirm the third hypothesis that pupil dilation would occur with increased perceived image attractiveness, further analysis was conducted to test the effects of possible confounding variables. Stimulus luminance and model face luminance were both tested as confounding variables on average pupil area change because pupil size is affected by target luminance; specifically, low luminance levels cause the pupil to dilate and high luminance levels cause the pupil to constrict (Laeng et al., 2012; Laeng & Endestad, 2011; Berman et al., 1996). To test whether stimulus luminance of the chair was associated with the change in average pupil area, a mixed model analysis of variance was run. The mixed model analysis of variance for change in pupil area tested stimulus luminance, overall image attractiveness ratings, gender, and designer status as fixed effects, with participant ID as a random effect (See Table 6.1.1. in Appendix B). Residual variability accounted for all of the total variability for change in pupil area. There was a significant main effect of stimulus luminance ($F(1,1012)=42.287$, $p=0.000$) (See Table 6.2.1. and Table 6.2.2. in Appendix B): participants' pupils constricted as stimulus luminance increased. However, when stimulus luminance was included as a covariate in the statistical model, overall image attractiveness ratings were still not significantly associated with change in average pupil area (See Table 6.2.1. in Appendix B) and no other main effects or interactions were statistically significant.

3.5 Pupil Area Change and Model Face Luminance

Model face luminance was also tested as a possible confounding variable of the change in pupil area. The mixed model analysis of variance for the change in average pupil area tested model face luminance, overall image attractiveness ratings, gender, and designer status as fixed effects, with participant ID as a random effect. Total variance for pupil area change was all residual variability (See Table 7.1.1. in Appendix B). Model face luminance did not have a significant main effect on change in average pupil area (See Table 7.2.1. in Appendix B). When model face luminance was included as a covariate in the statistical model, the association between overall image attractiveness ratings and change in average pupil area still was not significant (See Table 7.2.1. in Appendix B). Additionally, no other main effects or interactions were statistically significant.

3.6 Model Attractiveness and Model Face Luminance

As further analysis of why the results did not confirm the third hypothesis, the relationship between model face luminance and model attractiveness was tested because previous research has shown both luminance levels and attractiveness levels affect the pupil area (Laeng et al., 2012; Rieger & Savin-Williams, 2012; Laeng & Endestad, 2011; Berman et al., 1996; Hess & Polt, 1960). A mixed model analysis of variance was run to test whether model attractiveness was associated with model face luminance. The mixed model analysis of variance for model attractiveness tested model face luminance, gender, and designer status as fixed effects, with participant ID as random effects. Inter-individual variability accounted for 32% of the total variance for model attractiveness and 68% was residual variability (See Table 8.1.1. in Appendix B). The model face luminance had a significant main effect on model attractiveness ($F(1,477)=59.432$, $p=0.000$) (See Table 8.2.1. and Table 8.2.2. in Appendix B): high facial luminance was perceived as more attractive compared to low facial luminance. No other main effects or interactions were statistically significant.

3.7 Pupil Area Change and Number of Fixations

To further analyze why the results did not confirm the third hypothesis that pupil dilation would increase with perceived image attractiveness, the number of fixations was tested as a possible confounding variable on the change in pupil area. Previous research has shown that the number of fixations and pupil area increase with the degree of interest (Rieger & Savin-Williams, 2012; Buscher et al., 2009; Pan et al., 2004; Rayner, 1998; Hess & Polt, 1960), yet results from the present study indicate that the pupils did not dilate with increased interest. To investigate this difference, a mixed model analysis of variance for change in average pupil area tested number of fixations, overall image attractiveness ratings, gender, and designer status as fixed effects, with participant ID as a random effect. Residual variability accounted for 100% of the total variance for change in average pupil area (See Table 9.1.1. in Appendix B). The number of fixations was not a significant main effect on the change in average pupil area (See Table 9.2.1. in Appendix B). There were no significant differences between genders, designer status, or the two-way interactions (See Table 9.2.1. in Appendix B).

3.8 Pupil Area Change and Average Fixation Time

Also to further analyze the results of the third hypothesis, fixation time was analyzed as a possible confounding variable of pupil area change because previous research shows that fixation duration and pupil area are dependent on the difficulty of an image (Buscher et al., 2009; Pan et al., 2004; Rayner, 1998; Granholm et al., 1997; Just & Carpenter, 1993; Hess & Polt, 1964). A mixed model analysis of variance was run to test whether ln average fixation time affected the change in average pupil area. The mixed model analysis of variance for change in average pupil area tested ln average fixation time, overall image attractiveness ratings, gender, and designer status as fixed effects, with participant ID as a random effect. Residual variability accounted for 100% of the total variance for change in average pupil area (See Table 10.1.1. in Appendix B). The ln average fixation time did not have a main effect on the change in average pupil area (See Table 10.2.1. in Appendix B). Additionally, there were no significant gender or designer status differences in changes in average pupil area and ln average fixation time.

3.9 Model Attractiveness and Pupil Area Change

To test the second part of the third hypothesis that pupil area increases as model attractiveness increases, a mixed model analysis of variance was run. The mixed model analysis of variance for change in average pupil area tested model attractiveness, gender, and design status as fixed effects, with participant ID as a random effect. Residual variability accounted for all of the total variance for change in average pupil area (See Table 11.1.1. in Appendix B).

There was no significant main effect of model attractiveness on change in average pupil area (See Table 11.2.1. and Table 11.3.1. in Appendix B), nor were there other significant main effects or interactions.

3.10 Image Complexity and Pupil Area Change

A mixed model analysis of variance tested the fourth hypothesis, which predicted pupil area would decrease when viewing simple images and increase when viewing moderately complex images. The mixed model analysis of variance for change in average pupil area tested image complexity, gender, and designer status as fixed effects, with participant ID as a random effect. Residual variability accounted for all of the total variance for change in average pupil area (See Table 12.1.1. in Appendix B). There was a significant main effect of image complexity on change in average pupil area ($F(1,1010)=33.111$, $p=0.000$) (See Tables 12.2.1. and 12.2.2. in Appendix B): for moderately complex images, the pupils dilated by 2.53% (0.1944 mm^2), but for simple images the pupils further constricted 2.29% (-0.3119 mm^2) compared with viewing the white image, which is a total 4.82% difference (See Table 12.3.1. in Appendix B). No other main effects or interactions were statistically significant.

3.11 Image Complexity and Number of Fixations

To test the first part of the fifth hypothesis, which predicted an increase in image complexity would increase the number of fixation points, a mixed model analysis of variance was run. The mixed model analysis of variance for average number of fixations tested image complexity as a fixed effect, with participant ID as a random effect. Inter-individual variability accounted for 10% of the total variance for the average number of fixations and 90% was residual variability (See Table 13.1.1. in Appendix B). There was a main effect for image complexity on average number of fixations ($F(1,989)=34.57$, $p=0.000$): simple images elicited a significantly greater number of fixations (3.686) compared to complex images (3.326) (See Tables 13.2.1. and 13.2.2. in Appendix B).

3.12 Image Complexity and Average Fixation Time

The second part of the fifth hypothesis, which stated increased image complexity would decrease the average fixation time, was tested using a mixed model analysis of variance. The mixed model analysis of variance for ln average fixation time tested image complexity as a fixed effect, with participant ID as a random effect. Inter-individual variability accounted for 16% of the total variance for ln average fixation time and 84% was residual variability (See Table 14.1.1. in Appendix B). As predicted, there was a significant main effect of image complexity (F(1,979)= 25.252, p=0.000) (Tables 14.2.1. and 14.2.2. in Appendix B): for moderately complex images the ln average fixation time was approximately -1.047, while the ln average fixation time was approximately -9.56 for simple images. Therefore, fixations were considerably longer for moderately complex images than for simple images.

3.13 Average Fixation Time and Image Attractiveness

Results did not confirm the second part of the fifth hypothesis, which predicted increased image complexity would decrease average fixation duration, and consequently further analysis was conducted to explore whether image attractiveness was a confounding variable. Previous studies have shown that showed that fixation duration is lengthened when viewing a face (Nielsen & Pernice, 2010; Guo et al., 2006). Present results showed that moderately complex images, which include a face, are rated as more attractive To test whether participants had longer fixations when images were perceived as more attractive, a mixed model analysis of variance was run. The mixed model analysis of variance for ln average fixation time tested overall image attractiveness ratings, gender, and designer status as fixed effects, with participant ID as a random effect. Inter-individual variability accounted for 14.8% of the total variance for ln average fixation time and 85.2% was residual variability (See Table 15.1.1. in Appendix B). Ln average fixation time had a significant main effect on overall image attractiveness ($F(1,1015)=8.218$, $p=0.004$) (See Table 15.2.1. and Table 15.2.2. in Appendix B): images perceived as more attractive received longer fixation periods compared to images perceived as less attractive. There were no significant associations between gender, designer status, or two-way interactions (See Table 15.2.1. in Appendix B).

3.14 Image Complexity and Areas of Focus

3.14.1 Heatmaps

To test the sixth hypothesis that participants would primarily focus on the human model when viewing moderately complex images, and primarily focus on the chair when viewing simple images, heatmaps were generated for all 32 stimuli (simple and moderately complex images). Based on visual inspection, there appeared to be a large difference between moderately complex images and simple images. From these heatmaps, it was clear that all participants spent the largest amount of time fixating on the human model's face in moderately complex images and fixating on the seat of the chair in simple images. For all heatmaps, refer to Appendix A, Figures 4.1.1. through 4.16.2.

3.14.2 Lookzones

To further explore the sixth hypothesis, lookzones were generated for each of the moderately complex images. Thus, 64 images with 2 lookzones per stimulus (128 total lookzones) were analyzed. Each lookzone calculated the percentage of time spent viewing a specified image area relative to the time spent looking at the total image. For each moderately complex image, two lookzones were created to examine the percentage of time spent within each area of interest: the face of the human model and the chair. Lookzone data confirmed that the majority of time was spent looking at the human model's face when viewing a moderately complex image. As predicted, across all moderately complex images, participants spent an average of 62.35% of time looking at the face of the human model and only 37.65% of time looking elsewhere on the stimulus. In all cases when the human model was present, the participant spent less time looking at the chair and more time looking at the face of the human model. This also confirms what was observed from the heatmaps.

3.15 Gender Differences in Viewing Patterns

Heatmaps and a mixed model analysis of variance test run on lookzone data were used to test the seventh hypothesis, which predicted males would have fewer fixations, longer fixation durations, and different areas of focus compared to females. The mixed model analysis of variance for average number of fixations tested image complexity, gender, and the two-way interaction as fixed effects, with participant ID as a random effect. Inter-individual variability accounted for 10% of the total variance for average number of fixations and 90% was residual variability (See Table 13.1.1. in Appendix B). Contrary to the hypothesis there was no significant main effect of gender on average number of fixations (See Table 13.2.1. in Appendix B). There was a significant image complexity by gender interaction ($F(1,989)= 5.293$, $p = 0.022$) (See Figure 3.15.1 below and Table 13.2.1. in Appendix B). Male participants made significantly more fixations for simple images (3.832) compared moderately complex images (3.332) ($F(1,989)=33.458$, $p=0.000$). Female participants also made more fixations for simple images (3.539) compared to moderately complex images (3.32) ($F(1,989)=6.404$, $p=0.012$) (See Table 13.4.4 and 13.4.5. in Appendix B). However, for simple images male participants had a significantly greater number of fixations compared to female participants ($F(1,41)=4.098$, $p=0.049$) (Table 13.4.1. and Table 13.4.2. in Appendix B).

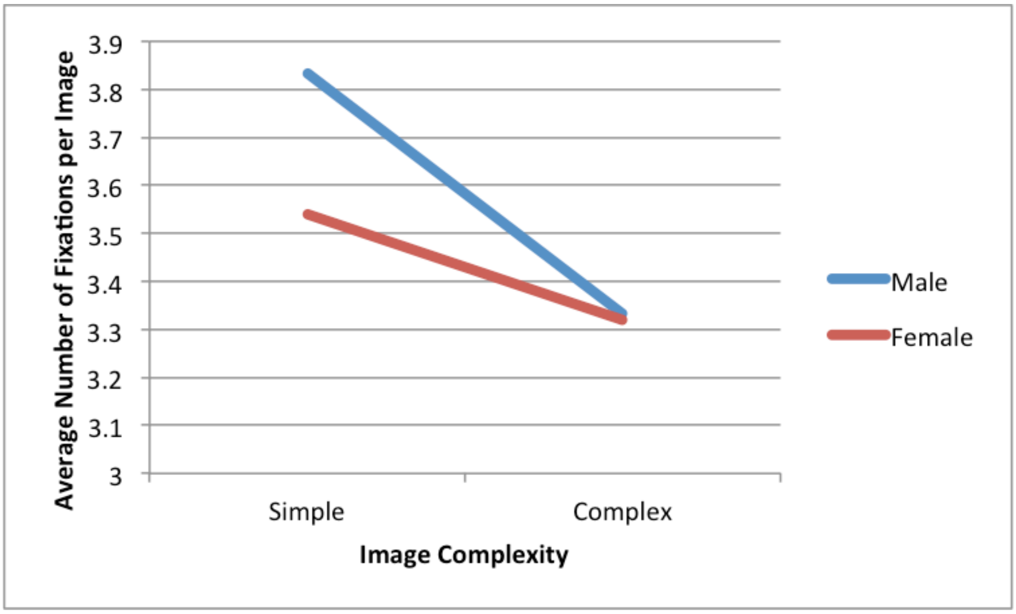

Figure 3.15.1: Interaction of Gender and Image Complexity for the Average Number of Fixations

Another mixed model analysis of variance for ln average fixation time tested image complexity, gender and the two-way interaction as fixed effects, with participant ID as a random effect. Inter-individual variability accounted for 16% of the total variance for ln average fixation time and 84% was residual variability (See Table 14.1.1. in Appendix B). There was no significant main effect of gender on ln average fixation time (See Table 14.2.1. in Appendix B). Additionally, there was no significant interaction between gender and image complexity for ln average fixation time (See Table 14.2.1. in Appendix B).

Heatmaps and lookzone data were used to determine whether males had different areas of focus compared to females. Based on visual inspection of heatmaps, there did not appear to be a large difference between where males and females were focusing on the stimuli (See Figures 4.1.1. through 4.16.2. in Appendix A). Lookzone data confirmed that there was no significant effect of gender: males spent on average 63.63% of time looking at the human model's face, while females spent on average 61.08% of time looking at the face of the human model when viewing moderately complex images.

3.16 Designer Status Differences in Viewing Patterns

Heatmaps, lookzone data and mixed model analysis of variance tests were used to test the eighth hypothesis, which predicts designers would have more fixations, shorter fixation durations, and different areas of focus compared to non-designers. The mixed model analysis of variance for average number of fixations tested image complexity, designer status, and the two-way interaction as fixed effects, with participant ID as a random effect. Inter-individual variability accounted for 10% of the total variance for average number of fixations and 90% was residual variability (See Table 13.1.1. in Appendix B). There was no significant main effect of designer status on the number of fixations (See Table 13.2.1. in Appendix B). However, there was a significant interaction of designer status by image complexity for the average number of fixations ($F(1,989)=5.591$, $p=0.018$) (See Figure 3.16.1. below and Table 13.2.1. in Appendix B). Designers made significantly more fixations when viewing simple images (3.707) compared to moderately complex images (3.203) (F(1,989)=33.983, p=0.000), whereas non-designers also made significantly more fixations on simple images (3.664) compared to moderately complex images (3.449) (F(1,989)=6.177, p=0.013) (Table 13.5.2. and Table 13.5.3. in Appendix B). There were no significant differences in number of fixations between the designers and the non-designers for simple images but a marginally statistically significant difference (F(1,42)=2.891; p=0.097) for moderately complex images (See Figure 3.16.1 below and Table 13.5.4. and Table 13.5.5. in Appendix B).

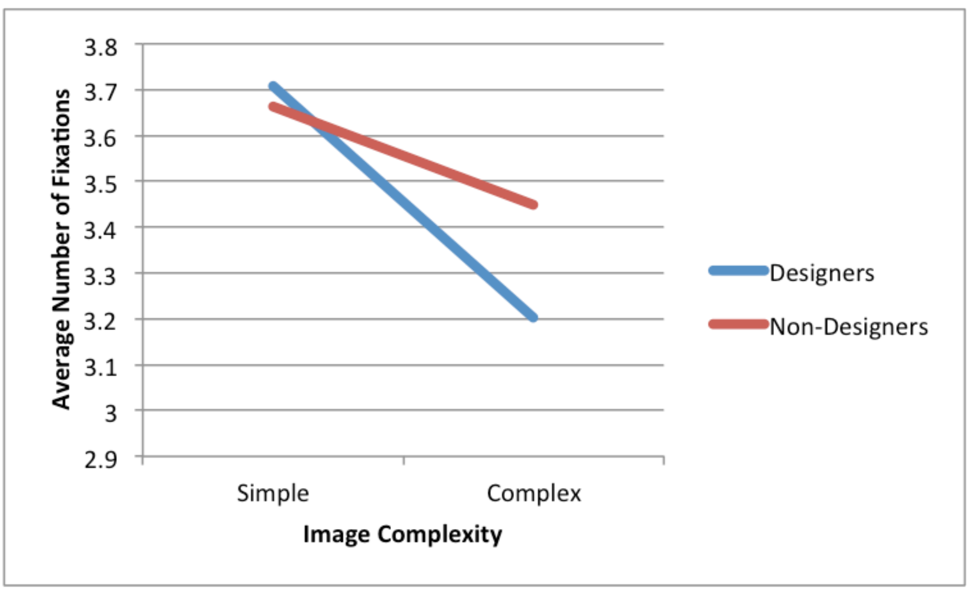

Figure 3.16.1: Interaction of Designer Status and Image Complexity on the Average Number of Fixations

Another mixed model analysis of variance for ln average fixation time tested image complexity, designer status, and the two-way interaction as fixed effects, with participant ID as a random effect. Inter-individual variability accounted for 16% of the total variance for ln average fixation time and 84% was residual variability (See Table 14.1.1. in Appendix B). There was no significant main effect of designer status on ln average fixation time (See Table 14.2.1. in Appendix B). However, there was an interaction between designer status and image complexity ($F(1,979)=5.036$, $p= 0.025$) (See Table 14.2.1. in Appendix B): the ln average fixation time was significantly higher for moderately complex images (-0.955) compared to simple images (-1.086) for designers ($F(1,988)=35.668$, $p=0.000$), but for non-designers, the difference in ln average fixation time for moderately complex images (-0.957) compared to simple images (-1.008) was not significant (See Figure 3.16.2 below and Table 14.4.1. and Table 14.5.2. in Appendix B). The difference between ln average fixation time for designers and non-designers was not significant for moderately complex images; however, for simple images the difference was marginally statistically significant ($F(1,36)=2.846$; $p=0.100$) (See Table 14.5.3. and Table 14.5.4 in Appendix B).

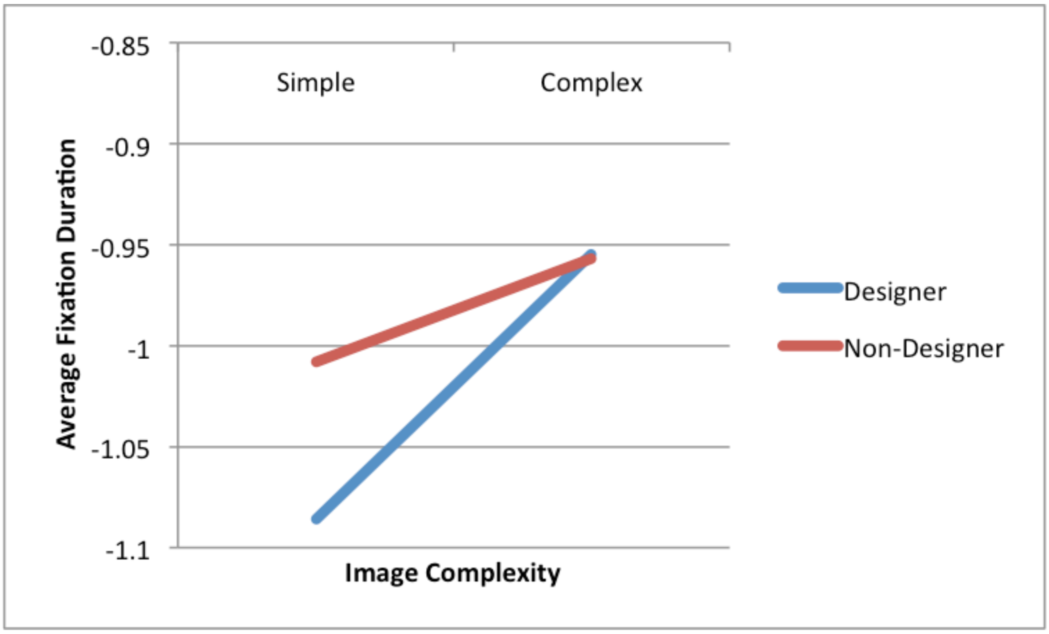

Figure 3.16.2: Interaction of Designer Status and Image Complexity on Ln Average Fixation Time

Heatmaps were used to determine whether designers had different areas of focus compared to non-designers. Based on a visual inspection of the heatmaps there appeared to be a difference between where designers and non-designers focused their attention. For simple images, designers appeared to view multiple areas of the chair compared to non-designers, who appeared to focus mostly on the seat of the chair (See Figures 4.1.1. through 4.16.2. in Appendix A).

Lookzone data also confirmed that designers spent more time looking at faces of human models compared to non-designers. Specifically, designers spent on average 57.375% of time looking at the human model's face, while non-designers spent on average 67.335% of time looking at faces of human models when viewing moderately complex images. Given that designers on average spent a smaller percentage of time looking at the human models' faces compared to non-designers, these results suggests that designers spent more time looking elsewhere on the image. Results support the eighth hypothesis that designers and non-designers focus on different areas of complex images.

3.17 Summary of Results

Four of the eight hypotheses were fully confirmed by the results above.

Hypothesis	Confirmed?
1. Moderately complex images will receive higher perceived attractiveness ratings compared to simple images.	Yes
2. The higher the perceived attractiveness rating of the human model, the greater the difference between the attractiveness ratings of the moderately complex image and the simple image.	Yes
3. (Part 1) Pupil dilation will increase as the perceived image attractiveness increases.	No
3. (Part 2) Pupil dilation will increase as the perceived model attractiveness increases.	No
4. Pupil constriction will occur when viewing simple images and dilation will occur when viewing moderately complex images.	Yes
5. (Part 1) Increased image complexity will increase the number of fixation points.	No
5. (Part 2) Increased image complexity will decrease average fixation durations.	No
6. The presence of a human model will attract more attention than the object alone.	Yes
7. (Part 1) Males will have fewer fixations compared to females.	No
7. (Part 2) Males will have longer fixation durations compared to females.	No
7. (Part 3) Males will have different areas of focus compared to females.	No
8. (Part 1) Designers will have more fixations compared to non-designers.	No
8. (Part 2) Designers will have shorter fixation durations compared to non-designers.	No
8. (Part 3) Designers will have different areas of focus compared to non-designers.	Yes

Table 3.17.1: Results Summary

CHAPTER 4: DISCUSSION

Selected images of various chairs with or without female human models were used to investigate whether the image complexity impacts the attractiveness of an image containing an ergonomic product (the chair). The effects of human model attractiveness, image complexity through human presence, and whether there are gender and designer differences were tested and are discussed in the following sections.

4.1 Image Complexity and Image Attractiveness

When a human model was present and the human model was looking at the camera in moderately complex images, the overall image was perceived to be significantly more attractive compared to simple images, which lacked the presence of a human model. This finding agrees with previous research showing that attractive faces activate reward regions in the human brain (Winston et al., 2007; Aharon et al., 2001); attraction is judged to be greater when human faces look directly at the camera (Nielsen & Pernice, 2010); sales increase when an attractive spokesperson represents a product (Dion, Berscheid, and Walster, 1972); and advertisement effectiveness increases when a physically attractive person presents (Petroshius & Croker, 1989; Caballero & Pride, 1984). Results from the present research affirmed the positive connection between a human model and attraction. In the current research, the only change to the complexity of the image was the addition of a human model and regardless of the human model's attractiveness, the image attractiveness increased when participants viewed moderately complex images compared to when participants viewed simple images.

4.2 Image Attractiveness and Model Attractiveness

Additionally, through the findings of the present study, which show the attractiveness of a human model in an image is positively associated with overall image attractiveness, the impact of an attractive human model in computer display media may be validated. Caballero and Pride's study (1984) used an attractive human model in direct mail advertisements and Petroshius and Croker's (1989) study used an attractive spokesperson on television advertisements, whereas the present study used a human model in images displayed on a computer screen. Results of the present research that show a positive effect of human model attractiveness on image attractiveness supported findings from Caballero and Pride's study (1984), which exhibited a positive impact of an attractive human model on product sales, and Petroshius and Croker's study (1989), which indicated an attractive spokesperson increased advertisement attractiveness. Given these numerous findings on the effect of human model attractiveness, there appears to be a universal positive effect of human model attractiveness across different media, such as mail, television, and computer displays.

4.3 Image Attractiveness and Pupil Area Change

The results of the present study show image attractiveness and change in average pupil area were not significantly associated, which conflicts with previous research that found pupil area was positively correlated with attractiveness (Rieger & Savin-Williams, 2012; Hess & Polt, 1960). The reason for the contrary findings between prior research and the present study is unclear; to understand these discrepancies, several confounding variables were considered. First, methodological differences of previous studies compared to the present study were explored. Hess & Polt's (1960) research was the first to establish correlation between attractiveness and pupil size based on measures of pupil diameter averaged across 20 frames per stimulus. Rieger & Savin-Williams (2012) found that pupil area, which is based on the number of the eye tracker's camera pixels occluded by the pupil, can be used as an objective measure of sexual attraction. Both Hess and Polt's study (1960) and Rieger and Savin-Williams' study (2012) found statistically significant pupil dilation when using sexually stimulating stimuli; no measure of sexual attraction was used in the present study. Though the attractiveness rating could be argued as a measure of sexual attractiveness, the stimuli used in the present study were less sexually stimulating. Hess and Polt (1960) showed participants a series of naked male and naked female images and Rieger and Savin-Williams (2012) showed participants a series of thirty-second video clips of either a naked male or a naked female performing a sexual act on themself, while the present study showed participants a series of images of a chair either alone or with a fully clothed human model. Further research comparing the impact of sexual verses non-sexual stimuli is warranted to further understand how image complexity altered through the presence of a human model affects viewers' perceived attractiveness and attention.

Another possibility is that contrary results were found because of differences in pupil measurement methods. Hess and Polt's (1960) study used a camera to take 20 photos of a participant's left eye as the participant viewed each stimulus, a projector to increase the size of the photos, and a ruler to manually measure pupil diameter, which is different from the automated eye tracking software used to calculate pupil area in the present study. Measuring fractions of millimeter differences by hand using a ruler may have led to human error in reading or recording pupil data, which would have impacted the reliability of Hess and Polt's (1960) findings. Additionally, the pupil data in Hess and Polt's (1960) study was captured at a much slower frame rate compared to the present study. While Hess and Polt (1960) captured pupil data

2 times per second, the present study captured pupil data 66 times per second, which is more accurate in detecting pupillary reactions that can occur within 0.2 seconds of viewing an image (Andreassi, 2007; Lowenstein & Loewenfeld, 1962). Weirda et al. (2012) found that high-temporal-resolution tracking (~10 Hz) is necessary to accurately capture pupillary responses; therefore Hess and Polt's (1960) technique for measuring pupil size was not fast enough to accurately capture pupillary responses. The difference between findings of Hess and Polt's (1960) study and the present study may be due to the differences in pupil measurement. The pupillary dilations found in Hess and Polt's (1960) study were measured using an inaccurate pupillometry tool, and may be the cause of the differing results between the two studies. However, both the present study and Rieger and Savin-Williams' (2012) study utilized an eye tracker of very high-temporal-resolution (~60 Hz), which allowed slow pupillary reactions to be accurately obtained from both eyes and then averaged together. Given Rieger and Savin-Williams' (2012) study and the present study used the same measurements but found contrary results, the number of frames captured per second is not likely a confounding variable in comparing the two studies.

Different gaze positions may have also been an unaddressed factor confounding of pupil measurements. Prior research has found that changes in gaze position systematically affect the measurement of pupil size (Gagl et al., 2011). For example, the shape of the measured pupil was elliptical when gaze was perpendicular to the screen (3 degrees relative to the center of the screen); however, the shape of the measured pupil becomes more circular as the viewer's gaze position changes to the left (toward the camera) (Gagl et al., 2011). Given that the position of the camera relative to the eye accounts for the particular shape of the pupil response, the present study attempted to account for this by adjusting the height of the table; however, the gaze angle was not directly measured. In future studies, gaze angle should be directly measured in future studies to ensure gaze position does not affect the measurement of pupil size.

Another issue may have been the duration of data collection in capturing a participant's initial reaction to a stimulus. In Rieger and Savin-Williams' (2012) study, pupillary responses to a stimulus were captured over a 30-second period, Hess and Polt's (1960) study captured pupillary responses over a 10-second timeframe, and in the present study, pupillary responses were captured over a 2-second period. Pupillary reactions to a visual image have been found to occur in as little as 0.2 seconds, with the pupillary response peaking from 0.5 to 1.0 seconds (Gagl et al., 2011; Andreassi, 2007; Beatty, 1982; Lowenstein & Loewenfeld, 1962). Immediately following the peak of the pupillary response, the pupil has been found to slowly recover back to the size prior to viewing stimuli (Privitera et al., 2008). Given that the pupil recovers back to size prior to viewing stimulus after the first second, capturing a pupillary response for an extended period of time after the peak pupil reaction may not be accurate in representing pupil size in response to a stimulus because the pupil size measurement will be averaged over the entire time, not just the peak pupillary response. Therefore, the extended duration of pupil data collection in Hess and Polt's (1960) study and Rieger and Savin-Williams' (2012) study may have been a confounding factor of pupil reaction to a stimulus because it is averaging pupil size over the entire period of time, not just the duration of the peak pupillary response. Future research may benefit from studying the peak of the pupillary response during the first 0.5 to 1 second period in order to capture the max dilation or constriction when viewing an image without including the time when the pupil constricts or dilates back to the size prior to viewing the stimulus. Prior research and the present study took measurements outside of this range, which may have lessened the peak pupillary responses to an image and been a confounding variable.

Lack of separation between stimuli has also been found to affect pupil size. Pupillary responses to two closely succeeding stimuli are found to overlap, because the pupil may not have time to return to the initial size (Weirda et al., 2012). Hess and Polt's (1960) study failed to temporally separate the viewing of one stimuli from another by showing one image directly after another without something neutral in between, whereas the present study separated tasks by inserting a 2-second white image between each stimulus. The overlap in Hess and Polt's (1960) study may have caused the pupil to have a bigger or smaller difference depending on whether the pupil was already dilated or already constricted from viewing the prior image, which would not provide accurate pupillary responses to a single image. However, the present study used the white images as separators to standardize the pupil size in order to prevent overlap of constriction or dilation from prior images. Through the use of the white images to standardize pupil size, the present study controlled for overlapping pupillary responses.

Another potential confounding variable that was explored through data analysis is the stimulus luminance, which was given by the luminance of the chair in simple images or the chair plus the human model in moderately complex images. Stimulus luminance was significantly negatively associated with the change in average pupil area. Extensive research on luminance influence on pupillary response has found high luminance levels decrease pupil size, while low luminance levels increase pupil size (Laeng et al., 2012; Laeng & Endestad, 2011; Berman et al., 1996), and therefore, stimuli luminance should be kept constant when studying additional influences on pupil size. Although the present study attempted to control for stimuli luminance by photographing stimuli in a windowless room, asking human models to wear a black coat and dark pants, and photographing in the same exact location; there were still differences such as the color of the chair that altered the luminance levels across images. Hess and Polt (1960) claimed stimulus luminance was "kept relatively constant" across images, while Rieger and Savin-Williams' study (2012) and the present study did not completely control for luminance across stimuli. The results showed that even when the confounding effect of stimulus luminance was included in the statistical analysis of the present study, image attractiveness ratings were still not significantly associated with change in average pupil area. This may indicate that physical factors, such as stimulus luminance, affect pupil size more than emotional factors, such as attractiveness. Further research is warranted to explore the significance of the effects of physical and emotion factors on pupillary responses.

Additionally, Laeng and Endestad (2011) found that pupillary responses to light reflect how bright or light a person thinks the visual image is, not just the amount of physical light energy entering the eye. Given that perceived brightness can affect pupillary responses, pupil research should consider this as a possible confounding variable. This is a limitation of the present study, which did not account for perceived luminance levels. Future research would benefit from asking participants for ratings of the perceived brightness of each image to determine whether it was a confounding variable on pupillary responses.

Facial luminance was also explored through data analysis as a potential confounding variable. Facial luminance, which is simply the luminance of the human model's face, is not the same as stimulus luminance, which is given by the luminance of the chair in simple images or the chair plus the human model in moderately complex images. Given that participants spent the most time viewing and fixating on the human model's face when the human model was present in the image and that high luminance causes pupils to constrict (Laeng et al., 2012; Laeng & Endestad, 2011; Berman et al., 1996), it is possible that the human model face luminance was a confounding factor on pupillary responses. Specifically, higher human model face luminance levels would have caused the pupils to constrict; however, the present research found there was no significant association between facial luminance and change in average pupil area. Although the present study explored whether facial luminance was a potential confounding variable through data analysis, it is unclear whether prior studies, such as Rieger and Savin-Williams (2012) or Hess and Polt's (1960), explored this potential confounding variable.

The side of the human model's face may have also been a confounding variable. Previous research has shown humans prefer to look at visual images of a person's left side of the face to the right side (Blackburn & Schirillo, 2012; Kowner, 1995). This preference occurs because the right hemisphere of the brain dominates perception and expression of emotions (Kowner, 1995). Given that one side of the face is preferred, the side of the face the human model shows will likely be a confounding variable on attractiveness ratings. In the present study, this left-face preference was not a confounding variable on attractiveness ratings because all of the human models showed the left side of their faces.

Additionally, the present study found human model attractiveness was positively associated with facial luminance. This finding agrees with prior research, which has indicated increased luminance enhances femininity and attractiveness in women's faces (Stephen & McKeegan, 2010). The current research adds to the understanding of what humans find attractive and further validates the relationship between luminance and human model attractiveness. Future research would benefit from knowing the ideal luminance contrast of the facial luminance and the luminance of the overall image. Knowing what the ideal luminance contrast is will further extend the understanding of what humans find attractive.

Additional variables, such as time-of-day and image sequence have been found to influence pupil size (Naber, et al. 2011; Loving et al., 1996). Over a 24-hour testing period, Loving et al. (1996) found a significant circadian rhythm for resting and maximum pupil diameter, but the pupil acrophases occurred randomly throughout the day with the largest portion of peaks occurring anywhere between 10:00AM and 10:00PM. Given the indication of circadian rhythms of the pupil, time-of-day could be a possible confounding factor. However, the present study controlled for this possible confounding variable by testing participants at various times throughout the day. Specifically, in order to prevent time-of-day from influencing pupillary responses, participants partook in the half-hour study at a chosen time of day anywhere between 9:00AM and 7:00PM. However, whether time-of-day was a confounding variable on pupillary responses was not explored in prior research, and therefore, may have been the reason for conflicting pupillary response results between the present study and prior studies.

Furthermore, pupil size has been found to increase more when viewing familiar images compared to novel images (Naber et al., 2011). Given that the stimuli in the present study were similar compositions in terms of the placement of a chair with or without a human model, it is possible that participants had increased pupil size as the familiarity of each composition became more anticipated. However, in the present study, all participants viewed the stimuli that were initially randomized, but then fixed so each participant viewed the same randomized sequence. Therefore, all participants would have been familiar with the same images in the same order. Whereas in prior research, the sequence that stimuli were viewed was a random order that was different for each participant; thus, familiarity may have altered pupillary responses differently for each participant due to the various stimuli sequence. Given that stimuli sequence was not the same for all participants in prior studies, familiarity of the images could not be controlled across participants, and thus, may have been a confounding variable on pupillary responses (Rieger & Savin-Williams, 2012; Hess & Polt, 1960). If the sequence was randomized for each subject, then researchers could not be certain that the pupils responded a specific way due to overlap of prior images or because of the specific image itself. Therefore, image sequence may account for some of the discrepancies in pupillary responses between the present study and prior studies.

In the present study, participants had unfamiliar with the human models prior to the study; therefore, recognition memory of the human models did not influence pupillary responses. However, the human models were shown in two different stimuli; this may have caused a novelty effect. Since familiarity increases pupil size (Otero et al., 2011; Naber et al., 2011; Kuchinke et al., 2007; Otero et al., 2006; Maw & Poplun, 2004), viewing the human models for the second time may have led to greater pupillary dilation relative to the initial viewing of the human model. Yet, in the present study, pupils were not found to dilate more for images with human models seen for the second time compared to the first time, which indicates there was no novelty effect. It is unclear whether prior studies considered a novelty effect when analyzing data (Rieger & Savin-Williams, 2012; Hess & Polt, 1960), which could have also contributed to the discrepancies in pupillary response measures found between studies.

Another area where there may have been a novelty effect is in the familiarity of chairs, as each chair was also shown in two different images. Unlike human model recognition, information on whether participants had previously seen any of the chairs that were used in the present study was not collected, though it was possible since the chairs were taken from a public space on campus. Given the extensive research that indicates pupils dilate when there is recognition of objects in a stimulus (Otero et al., 2011; Naber et al., 2011; Kuchinke et al., 2007; Otero et al., 2006; Maw & Poplun, 2004), it is likely that participants who had previously seen the chairs would have pupillary dilations when viewing those images. However, in this study, participants' pupils on average constricted when viewing simple images of chairs and dilated when viewing moderately complex images of chairs with human models, not when viewing a chair for a second time. Given that moderately complex images were not always shown first in the image sequence, it is not likely that the pupillary response was affected by recognition of chairs. Additionally, designers, who are more frequently see the chairs due to the location on campus, did not show increased pupil dilation when viewing chairs compared to non-designers when viewing the same chairs. Future research would benefit from testing recognition memory of all objects within the stimuli to ensure memory would not be a confounding factor.

Pupillary response has been found to provide a quantitative index of cognitive effort (Beatty and Lucero-Wagoner, 2000). Specifically, pupil size increases with cognitive effort, which increases with task difficulty (Granholm & Steinhauer, 2004; Granholm et al., 1997; Just & Carpenter, 1993; Hess & Polt, 1965). In the present study, rating the attractiveness of a chair may be less difficult compared to rating the attractiveness of a chair plus a human model. Therefore, task difficulty may also be a confounding variable on pupillary responses in the present study. If more cognitive effort was required to rate the attractiveness of moderately complex images compared to simple images, greater pupil dilation would be expected when viewing moderately complex images. Given that pupils did dilate when viewing moderately complex images and constricted when viewing simple images, cognitive effort may be a confounding factor in the present study.

The most probable explanations for the difference in the effect of pupillary responses between the present study and prior studies were the differences in the content of the stimuli, the differences in timeframe of capturing initial pupillary reaction, the inconsistency of luminance across stimuli, and the variance in cognitive effort. Although there are several factors that affect pupil response, such as memory, time-of-day, viewing sequence, and arousal, the present study controlled for these possible confounding factors in order to accurately determine the relationship between pupil area and perceived image attractiveness. However, the present study did not control for luminance across stimuli, which may have confounded the pupil data. Whether pupil area can be used as an objective measure of attractiveness of product images should be further researched with luminance held constant across all areas of all stimuli. Additionally, the content of the stimuli and the timeframe of data collection were two variables that differed between the present study and prior research, and may have been confounding variables on pupillary responses. Future research in this area would benefit from knowing how content (nude models vs. clothed models) of the stimuli affects pupillary responses and how duration of pupillary data collection impacts analysis of initial reaction to stimuli.

4.4 Image Complexity and Eye Movements

The addition of a human model to an image alongside a product moderately increases the complexity of the image (Tuch et al., 2009; Olivia et al., 2004). Results showed there were systematic differences in eye movement patterns on images of different levels of complexity. Given the extensive research that suggests eye movements vary by image complexity (Bradley et al., 2011; Guo et al., 2006; Weizmann, 1979), it was expected that more complex images would elicit more fixations. However, these expectations were only partially confirmed by the findings of the present research. In the present study, more complex images did elicit longer fixation durations, however, there were fewer fixations compared to simple images. A probable explanation for the discrepancy in the effect of image complexity on the number of fixations between the present study and previous studies may be due to length of time a participant viewed a stimulus. In Bradley et al.'s (2011) study, participants were given 6 seconds to freely view the image; in Guo et al.'s (2006) study there were 20 second viewing times for each image; whereas in the present study, participants were only given 2 seconds. Given that fixation durations typically last 200-300 milliseconds (Rayner, 1998), a 2-second timeframe may not have been long enough to determine whether more complex images elicit a significantly greater number of fixations. However, a 2-second timeframe was necessary to capture accurate initial pupillary responses; thus, future studies should test the complexity effect on number of fixations while viewing a stimuli and the complexity effect on initial pupillary reactions to a stimuli separately in order to utilize proper timeframes.

Furthermore, the addition of a human model may affect eye movement patterns differently than other techniques used to increase image complexity such as use of background colors or patterns (Geissler et al., 2006). Prior research that has found humans are drawn to other human faces (Nielsen & Pernice, 2010; Kelly et al., 2005; Johnson et al. 1991; Bryant, 1991; Fantz, 1963), and human faces elicit longer fixations compared to simple scenes (Guo et al., 2006; Mantyla & Holm, 2006; Yarbus, 1967). Additionally, fixation durations have been found to decrease with increased image complexity when viewing variations of computer displays (Goldberg, 2012; Nielsen & Pernice, 2010). Given prior research findings, the presence of a human model in images may elicit different eye movement patterns, such as fixation durations and areas of focus. Heatmaps and lookzones from the present study showed the human face in the moderately complex images captivated the majority of time and elicited longer fixations compared to simple images without a human model.

From the present study it is unclear whether the different eye movement patterns seen with the more complex images arose due to the presence of a human model or from the increase in complexity because these two factors were confounded. Given the present study found the opposite of Goldberg's (2012) findings on the relationship between fixation duration and image complexity, but aligned with prior research on the relationship between fixation duration and a human presence (Guo et al., 2006; Mantyla & Holm, 2006; Yarbus, 1967), it may be an indication the human presence affects fixation duration greater than image complexity. Future studies would benefit from testing how a human model affects eye movements compared to other variations of image complexity, such as the addition of objects or the use of patterns and colors, and whether one form of complexity has a greater affect on fixation duration. Additionally, future research would benefit from testing how a person standing behind or next to a product alters eye movement patterns compared to a human model in front of the product. Since visual complexity of an image has been found to depend on the viewer's ability to group objects (Olivia et al., 2004), having the human model separated from the product, rather than grouped with the product, may elicit different eye movements. Additional research is necessary to establish a better understanding of how different variations of complexity alter areas of focus.

In the present study, average fixation time was also significantly positively associated with image attractiveness. With a fixation, a viewer is cognitively processing and focusing more closely on details in the image (Granholm et al., 1997; Just & Carpenter, 1993; Hess & Polt, 1964). Additionally, while learning unfamiliar faces, participants have been found to elicit longer fixations in a single central location (Henderson et al., 2005). Given that the present study showed stimuli of unfamiliar faces and that results indicated participants showed longer fixations on these unfamiliar faces, it can be inferred that participants spent more time on the faces to analyze and learn the details of the image. Furthermore, the results of the present study indicated significantly longer fixations while viewing images deemed attractive, which may infer participants spend more time analyzing and viewing images deemed attractive.

4.5 Gender Differences in Viewing Patterns

Results from the present study showed there were gender differences in the perceived attractiveness of images and the number of fixations when participants viewed moderately complex images. Specifically, females rated simple images more attractive and had fewer fixations compared to males, whereas males rated moderately complex images more attractive and had fewer fixations compared to females.

Gender differences in image attractiveness ratings may be due to the varying impact of the human model used to alter image complexity. Prior research has found that females exhibit greater variability in attractiveness ratings compared to males (Townsend & Wasserman, 2013; Reis et al., 1980; Berscheid and Walster, 1974). Since males are more likely to seek sexual relations, they tend to rate females models more leniently compared to females (Towsend & Wasserman, 2013). Given that males rate female attractiveness higher than females, it is plausible that in this study males rated images with a female model present more attractive than females. These findings may indicate a difference in the effect of human models on image attractiveness between genders. However, it is unclear whether males perceived moderately complex images more attractive because of increased complexity or because of the presence of a human model, in this case a female who may have been of sexual interest. It would be interesting to measure how male and female participants differ in attractiveness ratings when viewing images including both male models and female models. Additionally, it would be interesting to measure how males and females differed in attractiveness ratings when viewing stimuli of various complexity levels without the presence of humans. Future studies would benefit from testing how attractiveness ratings of stimuli varying in complexity and the effect of the presence of human models of both sexes differ amongst male and female participants.

Prior research has also indicated the gender of the human model influences male and female duration of fixations (Rennels & Cummings, 2013; Nummenmaa et al., 2012; Anderson et al., 2012; Pan et al., 2004). More specifically, male participants have been found to fixate on female models longer than female participants, while female participants have been found to fixate longer on male models (Rennels & Cummings, 2013; Nummenmaa et al., 2012). These findings suggest the gender of a human model may be a confounding factor of fixation durations amongst males and females. The present study controlled for this potential confounding effect by only including female models in the stimuli, and found no fixation duration differences between genders.

Results from the present study may also indicate an influence of image complexity on the number of fixations between males and females. Prior research has found female models elicit more fixations compared to male models from participants viewing images of human faces (Rennels & Cummings, 2013). Given that participants focused primarily on the face of the human model in moderately complex images, this evidence provides a probable explanation as to why the number of fixations differs between genders when viewing moderately complex stimuli. The present study was congruent with prior research and further validated the gender difference effect of number of fixations on human stimuli.

In simple images with no human model present, the results of the present study found the opposite effect. Specifically, male participants elicited more fixations compared to female participants when viewing simple images. Prior research exploring the gender effect on number of fixations on simple images, such as geometric shapes, has shown females fixate fewer times compared to males (Miyahira et al., 2000; Miyahira et al., 1999). The findings from the present research are consistent with prior research and further validate a gender effect on number of fixations on simple images.

4.6 Designer Status Differences in Viewing Patterns

Results showed there were differences in number of fixations, fixation durations, and areas of focus between design students and non-design students; while change in pupil area and overall image attractiveness ratings were not significantly different between designers and non-designers. Prior research found that when viewing stimuli, people without an artistic background had a greater number of shorter fixations compared with those with an artistic background (Vogt & Magnussen, 2007; Nodine et al., 1993). In the present study, results aligned with prior studies when viewing simple images, but not when viewing moderately complex images. Specifically, designers had significantly more fixations and shorter fixation durations when viewing simple images compared to non-designers, but when viewing moderately complex images, designers exhibited fewer, longer fixations compared to non-designers.

One possible explanation for the discrepancies between prior studies and the present study is the difference in time allotted for viewing each stimulus. Nodine et al.'s (1993) study allotted 12 seconds and Vogt and Magnussen's (2007) study allotted 40 seconds for each stimulus to be viewed, whereas the present study only allotted 2 seconds. As previously discussed in the image complexity section above, fixations last approximately 200-300 milliseconds (Rayner, 1998), therefore, a 2-second timeframe may not be long enough to determine significant fixation differences between designers and non-designers. Contrarily, the 40-second viewing timeframe for each stimulus in Vogt and Magnussen's (2007) study may be too long of a timeframe, and allowing participants to become aware of areas they are viewing, making their fixations voluntary rather than being involuntary responses to the image (Smith and Henderson, 2009). Given the different effects of time on fixation data, future research would benefit from knowledge of what the ideal timeframe is in order to obtain accurate involuntary fixation data.

Prior studies that have utilized gaze trails and heatmaps have found that artists have scattered viewing patterns in order to capture the entire visual image, while non-artists focus on specific areas of an image to get the general idea (Zangemeister et al., 1995; Nodine et al., 1993). However, there may be a confounding factor of art-emphasized stimuli on eye movement scanning patterns, as used in the previous studies. Nodine et al. (1993) used famous paintings and Zangemeister et al. (1995) used abstract and realistic paintings, while the present study expanded visual images to photographs of realistic items with or without a human model. The present study found designers had more scattered viewing patterns on simple images, but non-designers had more scattered viewing patterns on moderately complex images. These findings may indicate beyond art-emphasized stimuli, designer and non-designer viewing patterns may not be as clear-cut. Additionally, prior research does not assess the complexity level of each stimulus, which may also have a confounding effect on designer status fixations and viewing pattern differences. Though it is unclear whether designer status viewing patterns differed due to influence of variation in complexity, a human model presence, or art-emphasized stimuli, any or all variables may be confounding factors. Future research would benefit from knowing how each of these variables influences designers' and non-designers' viewing patterns in order to further understand how to predict where participants will view a stimulus.

CHAPTER 5: CONCLUSION

Building on previous research, the present study is the first to more specifically investigate the impact of image complexity through the combined presence of a human model with a product on the attractiveness of an image overall, and the added impact of the attractiveness of the human model. Prior research only analyzed product sales, whereas the present study evaluated the attractiveness of the image itself and the human model itself and found the actual presence of a human model increased image attractiveness, and also more attractive the human model, the more attractive the image was perceived. Thus, the presence of a human model used to increase image complexity and the attractiveness of a human model can have a positive impact on advertising in that a human model increases the perceived attractiveness of the overall advertisement.

This research is also the first to study whether pupil area could be used as an objective measure in the determining of the impact of combining a human model with a product in an image. Previous research only saw pupil dilation when viewing sexually attractive stimuli, whereas the present study used non-sexually arousing stimuli and found no effect of image attractiveness on pupil size. Thus, the insignificant association of change in average pupil area and image attractiveness indicated pupil area could not be used as an objective measure of attractiveness; however, there were confounding variables, such as content of stimuli, stimulus luminance, duration of measurements, and task difficulty, that were not accounted for in the present study, which warrants further research. Although luminance of the image influenced pupillary reactions while viewing stimuli, the present study may have shown a possible greater effect of physical attributes over aesthetic attributes on pupil size. Research on pupillary response to image attractiveness thus far has predominantly used sexually arousing stimuli, overlooking the broader application of pupillary response to images of other stimuli such as ergonomic products. If an attractive human presence increases image attractiveness then this could enhance how ergonomic products are displayed.

In addition, the present study adds to the body of eye movement research because image complexity was shown to systematically affect the number, duration, and location of fixations. This gives further insight into predicting how a spectator will view an image and what elements attract the viewer's attention. Furthermore, the present study provides empirical evidence for eye movement differences between genders and designer status. These findings will be useful in the design and marketing worlds, where ergonomic products are intended to be displayed and viewed in the most attractive way.

However, there are several limitations to this study. First, there were some limitations with the experimental procedure and design of the study. The images used as stimuli in this study were of 16 different designer chairs. A broader array of various product categories should be investigated to increase the general usability of the results to further explore whether pupil area is a universal objective measure of product attractiveness. Additionally, a broader array of human models should be investigated to determine how the gender (Nummenmaa et al., 2012), age (Mazis et al., 1992) or ethnicity (Goldinger et al., 2010) of the human model plays a role in the effect on attractiveness and pupil area.

The stimuli used in this study were not of constant luminance levels; thus, the transition in luminance levels between images may have influenced pupillary responses. Future research should use stimuli of equal luminance levels to prevent an effect of luminance on pupil area.

Additionally, to provide further evidence that image complexity effects eye movement patterns, a broader array of image complexity levels should be further explored. In this study, complexity was increased by existence of the human model in the image; however, complexity can be increased by adding moving objects, more products and/or text, different sized objects, etc.

(Petersen & Nielsen, 2002). This will provide additional evidence on whether image complexity affects eye movement patterns.

Finally, future studies would benefit from expanding the types of participants. The present study used university students as participants, who are not representative of the full spectrum of the general population in terms of age, ethnicity, occupation, and so on, and this may limit the generalizability of the findings. Additionally, pupil reactions may differ between older and younger generations, as elderly pupillary reflexes may not occur as quickly (Andreassi, 2007; Kasthurirangan & Glasser, 2006; Van Gerven et al., 2004). Future studies could investigate possible effects of ethnicity (He et al., 2009), iris color (Bradley et al., 2010; Bergamin et al., 1998), or diseases or mental imparities (such as Alzheimer's, Parkinson's, or Schizophrenia) (Dietz et al., 2011; Granholm et al., 2003; Zahn et al., 1991) when exploring pupillary reactions, attractiveness ratings, or eye movement patterns.

While there were multiple limitations within the present study, it provides a starting point for the exploration of whether pupil area can be an objective measure of perceived attractiveness, how image complexity through the presence of a human model and how attractiveness of a human model affect the perceived attractiveness of a visual image, and how the complexity of an image systematically affects eye movement patterns. Results provide initial evidence that pupil area changes do not indicate perceived image attractiveness; human model presence in moderately complex images and the attractiveness of the human model increase overall image attractiveness; and an increase in image complexity lengthens the duration of fixations, decreases the number of fixations, and dilates the pupil. Overall, the present study adds to the understanding of the significance of image complexity through human presence, perceived attractiveness, and eye-tracking research, and broadens the platform for creating attractive, effective, and successful promotional designs.

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APPENDIX A: FIGURES

Figure 1.1.1. Bertoia Chair by Knoll

Figure 1.1.2. Bertoia Chair by Knoll with Model

Figure 1.2.1. Audio Chair by Bernhardt

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Figure 1.3.1. Risom Lounge Chair by Knoll

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Figure 1.4.1. Arm Navy Chair by EMECO

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Figure 1.5.1. Shell Chair by Herman Miller

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Figure 1.6.1. Coalesse Chair by Steelcase

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Figure 1.7.1. Aeron Chair by Herman Miller

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Figure 1.9.1. Panton "S" Chair by Knoll

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Figure 1.13.1. Saarinen Executive Chair by Knoll

Figure 1.13.2. Saarinen Executive Chair by Knoll with Model

Figure 1.14.1. Freedom Chair by Humanscale

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Figure 1.15.1. World Chair by Humanscale

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Figure 1.16.1. Mirra Chair by Herman Miller

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Figure 2.1.1. Headshot of Model in Images with Arm Navy Chair and Risom Lounge Chair

Figure 2.2.1. Headshot of Model in Images with Panton "S" Chair and Gubi 5 Chair

Figure 2.3.1. Headshot of Model in Images with Setu Chair and Series 7 Chair

Figure 2.4.1. Headshot of Model in Images with Saarinen Executive Chair and Mirra Chair

Figure 2.5.1. Headshot of Model in Images with Aeron Chair and Freedom Chair

Figure 2.6.1. Headshot of Model in Images with Ultimate Executive Highback Dual-Flex Chair and World Chair

Figure 2.7.1. Headshot of Model in Images with Bertoia Chair and Audio Chair

Figure 2.8.1. Headshot of Model in Images with Shell Chair and Coalesse Chair

Figure 3.1.1. Change in Average Pupil Area No Outliers Histogram

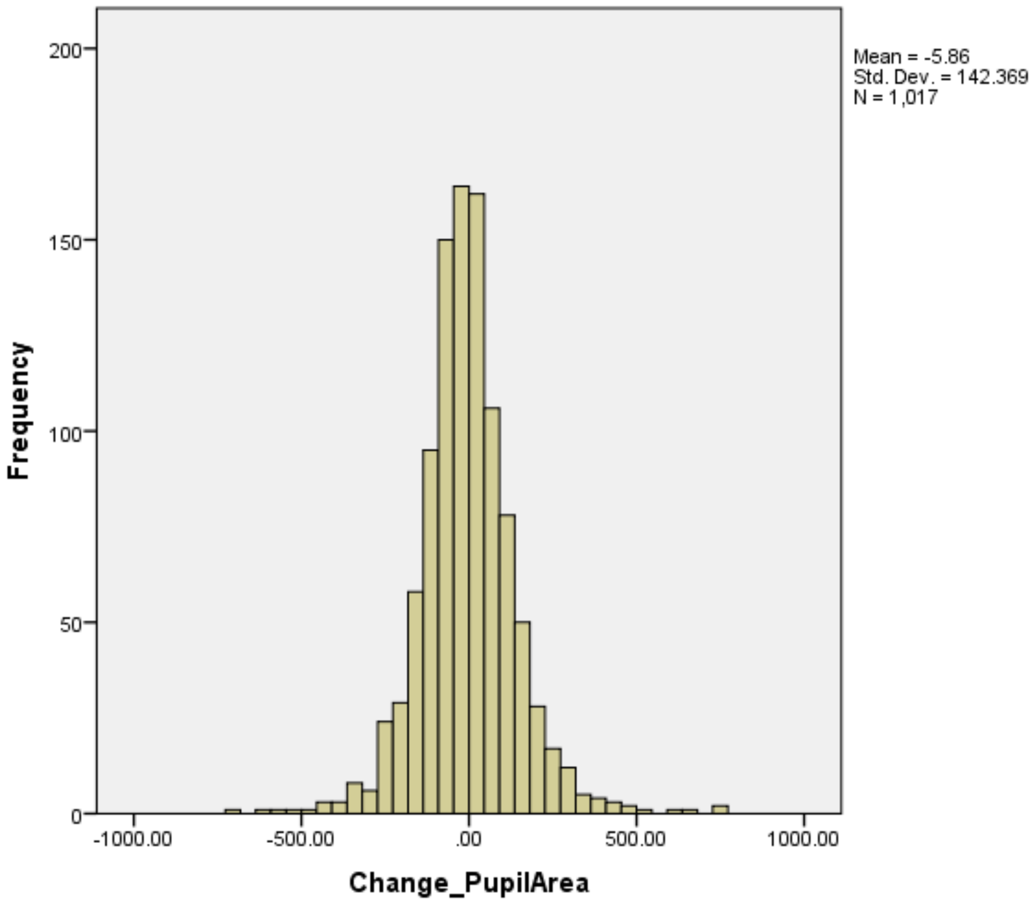


Figure 3.1.2. Image Attractiveness Ratings Histogram

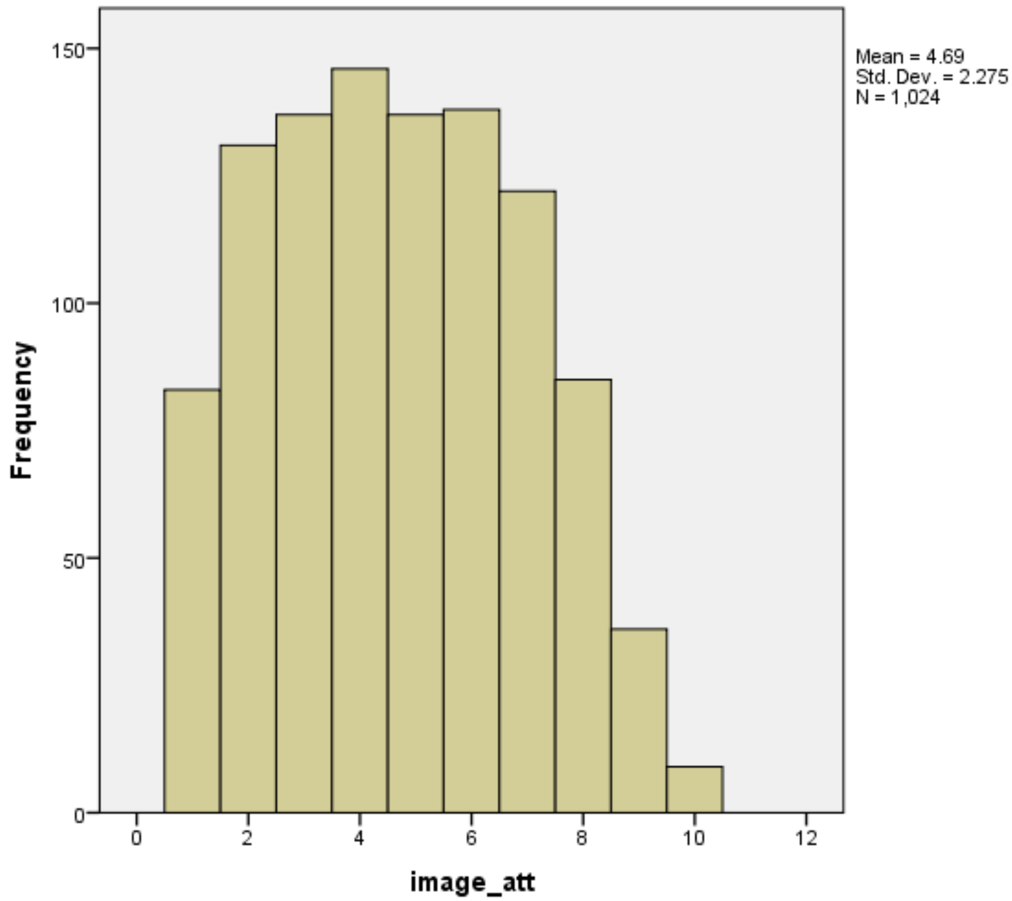


Figure 3.1.3. Model Attractiveness Ratings Histogram

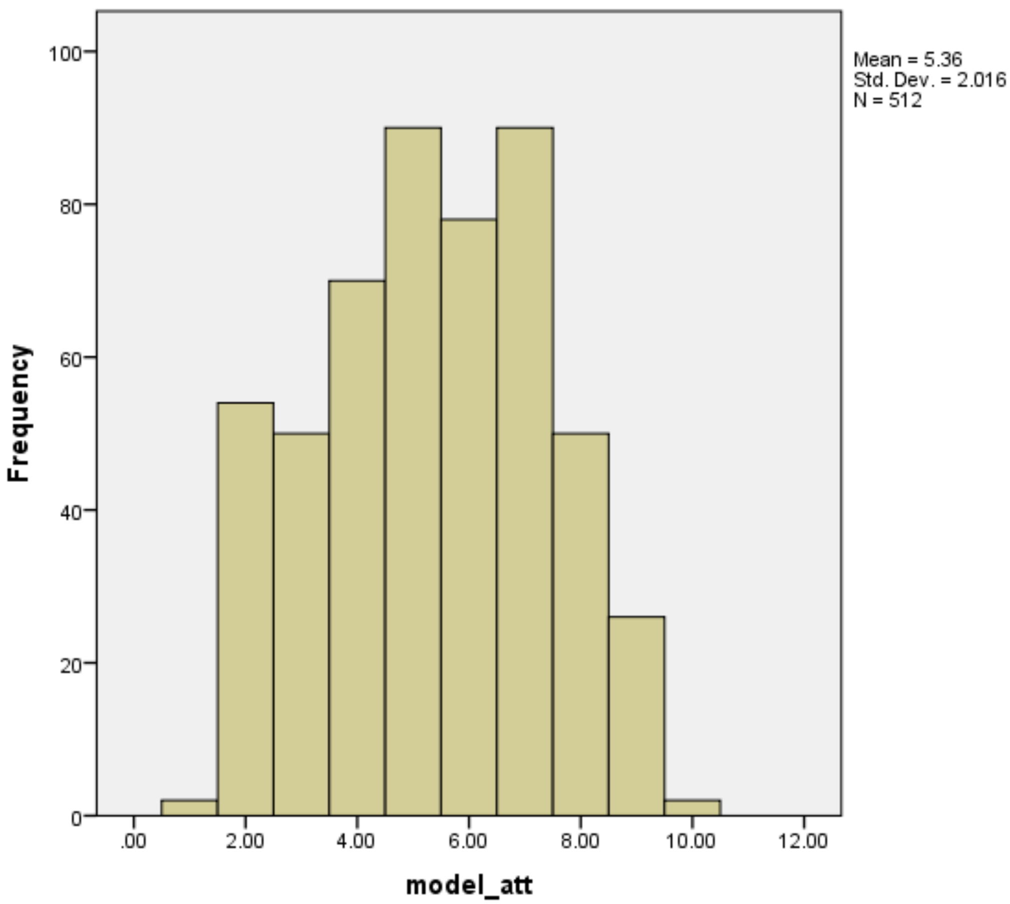


Figure 3.1.4. Number of Fixations Histogram

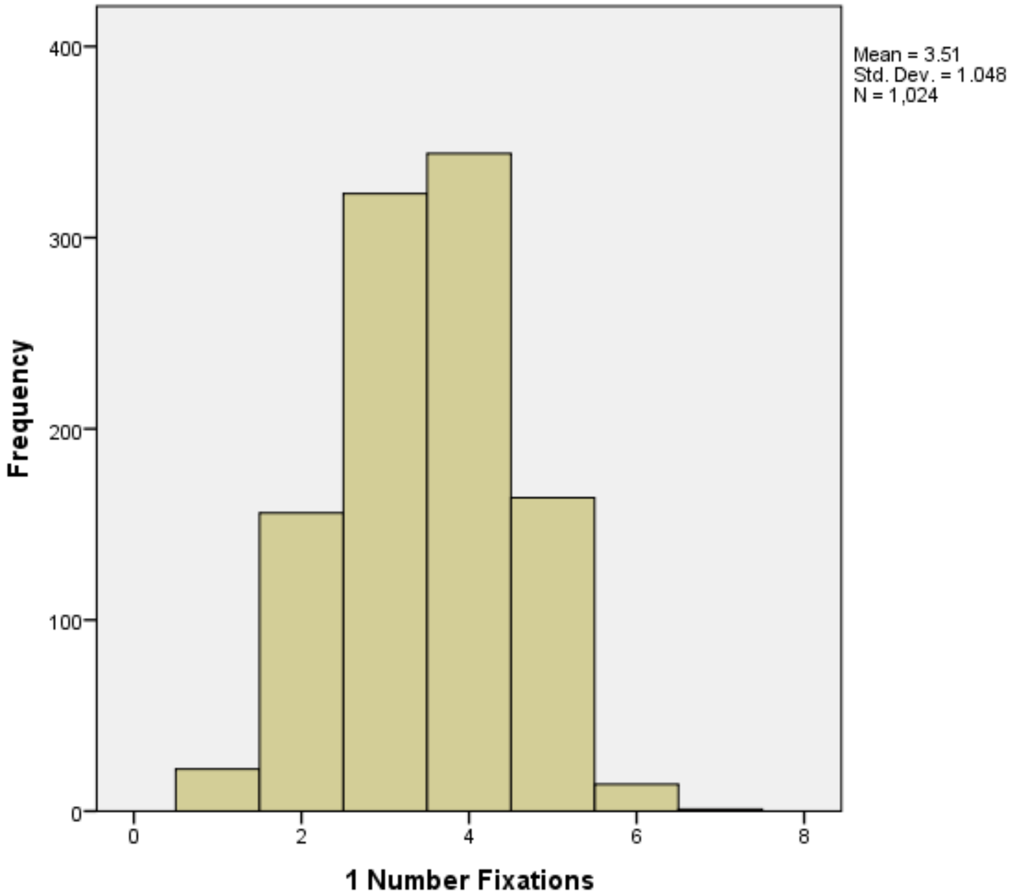


Figure 3.1.5. Log Average Fixation Time Histogram

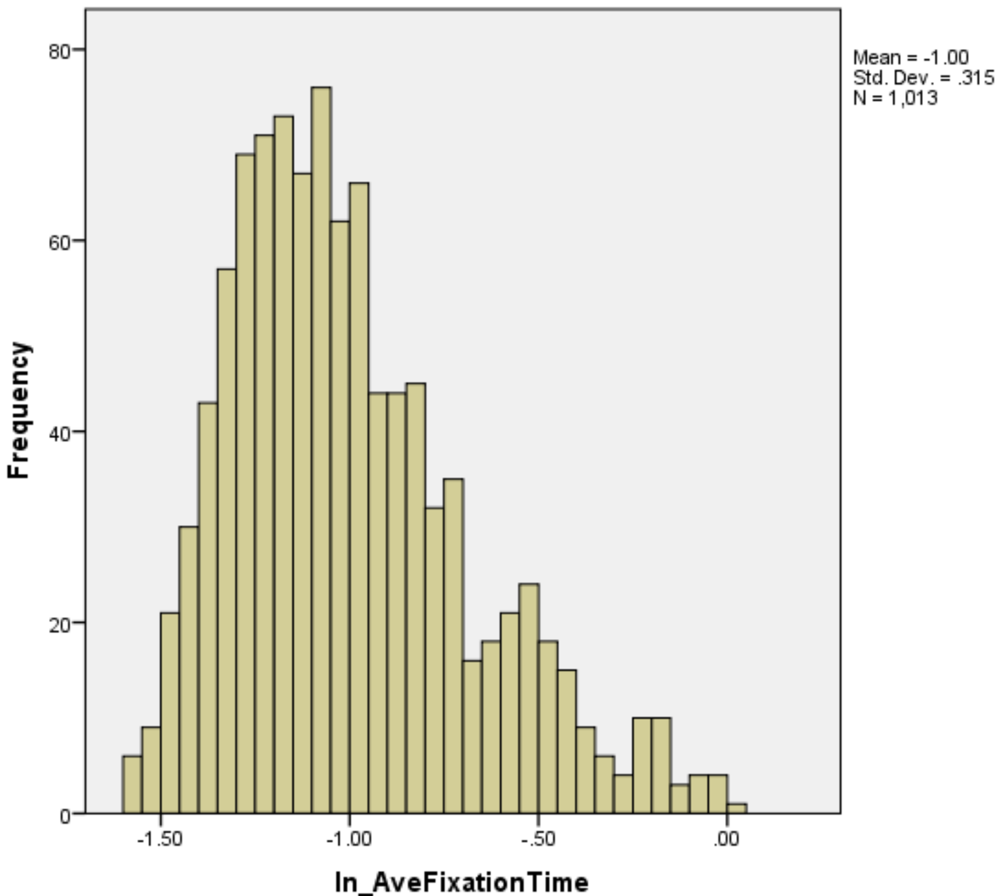
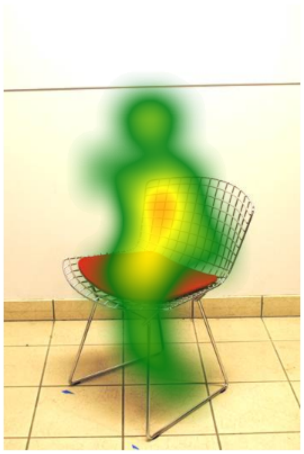
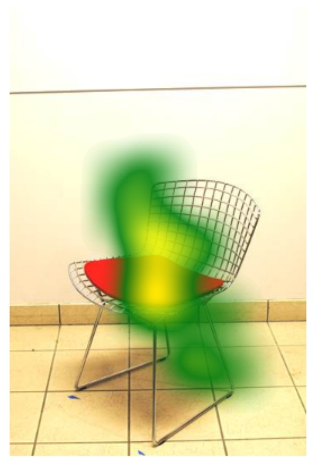


Figure 4.1.1. Heatmaps: Bertoia Chair by Knoll

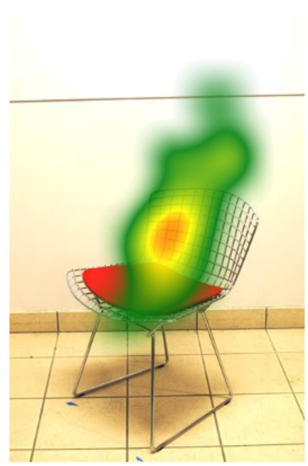


Female Designers



Male Designers

Female Non-Designers

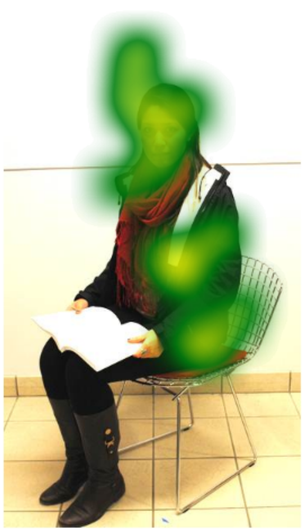


Male Non-Designers

Figure 4.1.2. Heatmaps: Bertoia Chair by Knoll with Models

Female Designers

Male Designers

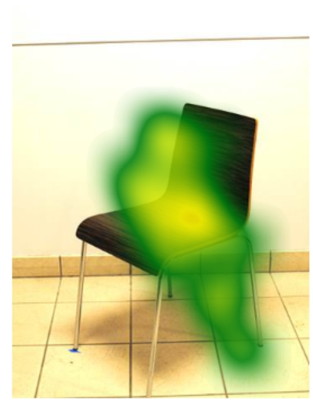


Female Non-Designers

Male Non-Designers

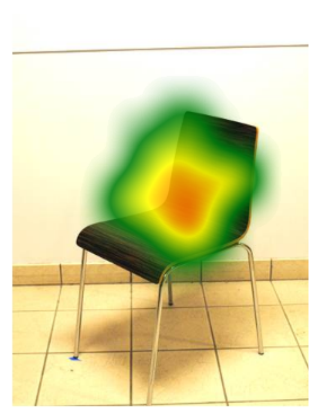
Figure 4.2.1. Heatmaps: Audio Chair by Bernhardt

Female Designers



Male Designers

Female Non-Designers



Male Non-Designers

Figure 4.2.2. Heatmaps: Audio Chair by Bernhardt with Models

Female Designers

Male Designers

Female Non-Designers

Male Non-Designers

Figure 4.3.1. Heatmaps: Risom Lounge Chair by Knoll

Female Designers

Male Designers

Female Non-Designers

Male Non-Designers

Figure 4.3.2. Heatmaps: Risom Lounge Chair by Knoll with Model

Female Designers

Male Designers

Female Non-Designers

Male Non-Designers

Figure 4.4.1. Heatmaps: Arm Navy Chair by EMECO

Female Designers

Male Designers

Female Non-Designers

Male Non-Designers

Figure 4.4.2. Heatmaps: Arm Navy Chair by EMECO with Model

Female Designers

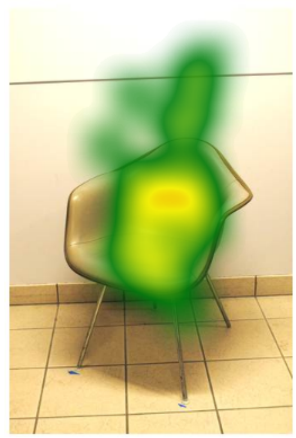
Male Designers

Female Non-Designers

Male Non-Designers

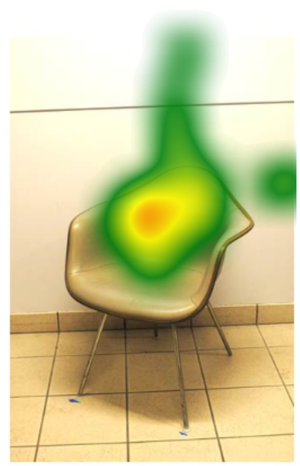
Figure 4.5.1. Heatmaps: Shell Chair by Herman Miller

Female Designers



Male Designers

Female Non-Designers



Male Non-Designers

Figure 4.5.2. Heatmaps: Shell Chair by Herman Miller with Model

Female Designers

Male Designers

Female Non-Designers

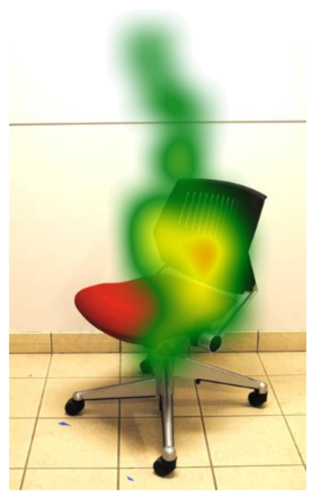
Male Non-Designers

Figure 4.6.1 Heatmaps: Coalesse by Steelcase

Female Designers

Male Designers

Female Non-Designers



Male Non-Designers

Figure 4.6.2. Heatmaps: Coalesse by Steelcase with Model

Female Designers

Male Designers

Female Non-Designers

Male Non-Designers

Figure 4.7.1. Heatmaps: Aeron Chair by Herman Miller

Female Designers

Male Designers

Female Non-Designers

Male Non-Designers

Figure 4.7.2. Heatmaps: Aeron Chair by Herman Miller with Model

Female Designers

Male Designers

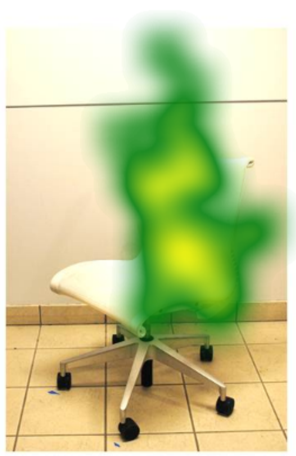
Female Non-Designers

Male Non-Designers

Figure 4.8.1. Heatmaps: Setu Chair by Herman Miller

Female Designers

Male Designers



Female Non-Designers

Male Non-Designers

Figure 4.8.2. Heatmaps: Setu Chair by Herman Miller with Model

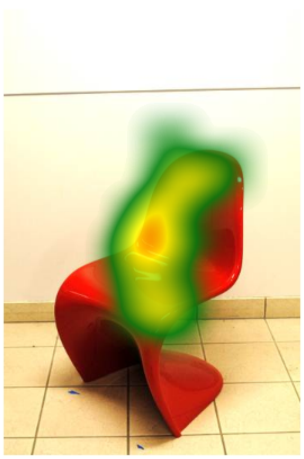
Female Designers

Male Designers

Female Non-Designers

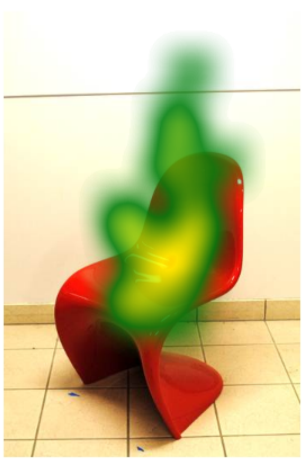
Male Non-Designers

Figure 4.9.1. Heatmaps: Panton "S" Chair by Knoll



Female Designers

Male Designers



Female Non-Designers

Male Non-Designers

Figure 4.9.2. Heatmaps: Panton "S" Chair by Knoll with Model

Female Designers

Male Designers

Female Non-Designers

Male Non-Designers

Figure 4.10.1. Heatmaps: Series 7 Chair by ICF

Female Designers

Male Designers

Female Non-Designers

Male Non-Designers

Figure 4.10.2. Heatmaps: Series 7 Chair by ICF with Models

Female Designers

Male Designers

Female Non-Designers

Male Non-Designers

Figure 4.11.1. Heatmaps: Gubi 5 Chair by Gubi

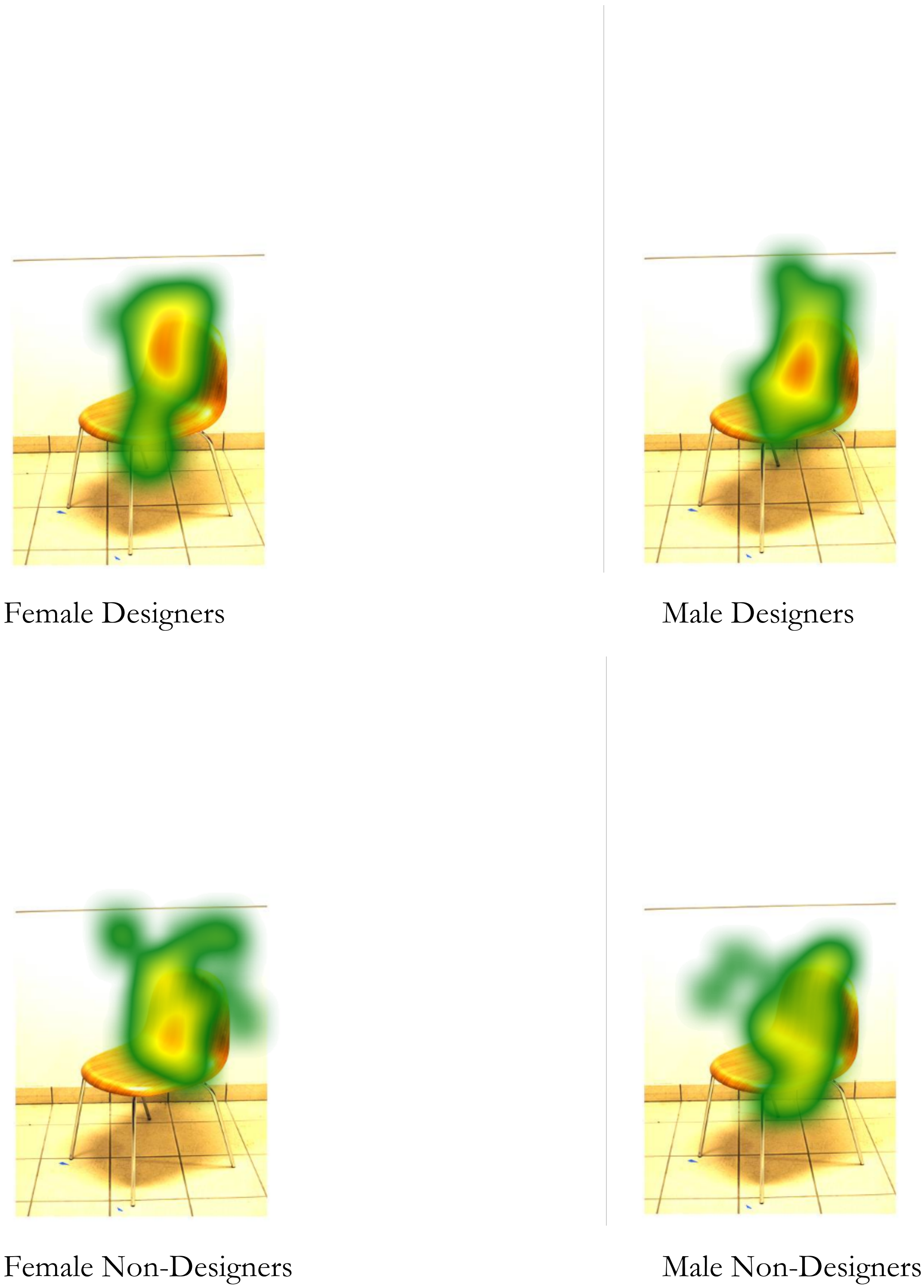
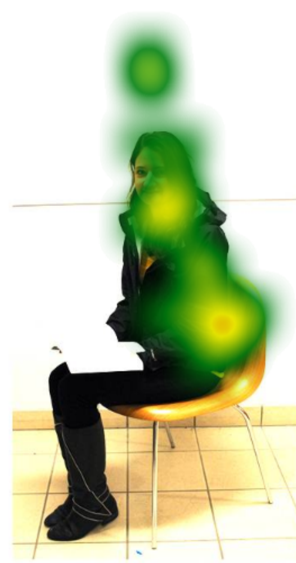


Figure 4.11.2. Heatmaps: Gubi 5 Chair by Gubi with Model

Female Designers

Male Designers

Female Non-Designers



Male Non-Designers

Figure 4.12.1 Heatmaps: Ultimate Executive Highback with Dual-Flex by Lifeform

Female Designers

Male Designers

Female Non-Designers

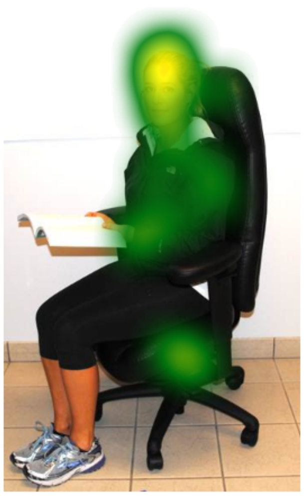
Male Non-Designers

Figure 4.12.2. Heatmaps: Ultimate Executive Highback with Dual-Flex by Lifeform with Model

Female Designers

Male Designers

Female Non-Designers



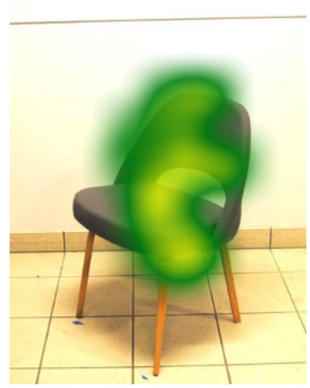
Male Non-Designers

Figure 4.13.1. Heatmaps: Saarinen Executive Chair by Knoll

Female Designers

Male Designers

Female Non-Designers



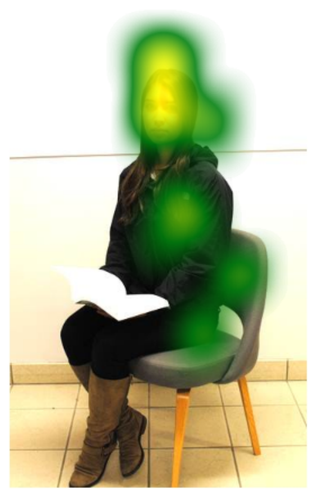
Male Non-Designers

Figure 4.13.2. Heatmaps: Saarinen Executive Chair by Knoll with Model

Female Designers

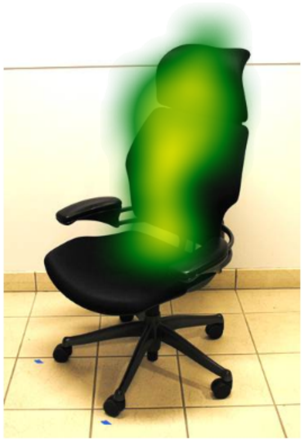
Male Designers

Female Non-Designers



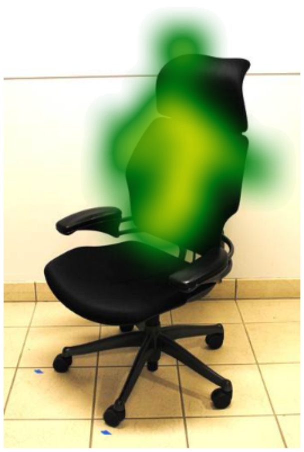
Male Non-Designers

Figure 4.14.1. Heatmaps: Freedom Chair by Humanscale



Female Designers

Male Designers



Female Non-Designers

Male Non-Designers

Figure 4.14.2. Heatmaps: Freedom Chair by Humanscale with Model

Female Designers

Male Designers

Female Non-Designers

Male Non-Designers

Figure 4.15.1. Heatmaps: World Chair by Humanscale

Female Designers

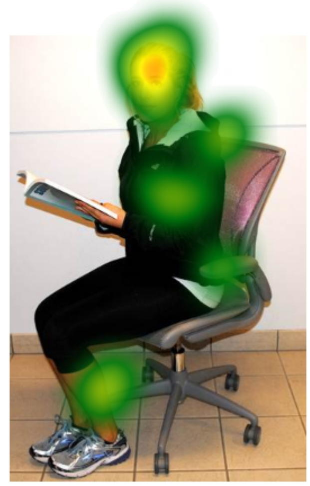
Male Designers

Female Non-Designers

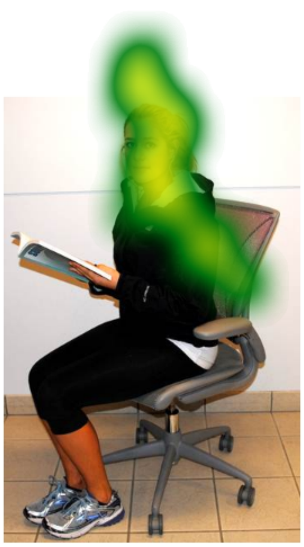
Male Non-Designers

Figure 4.15.2. Heatmaps: Freedom Chair by Humanscale with Model

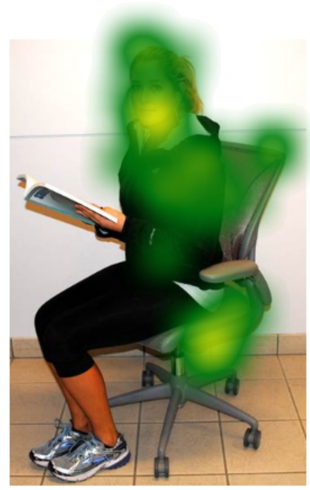
Female Designers



Male Designers



Female Non-Designers



Male Non-Designers

Figure 4.16.1. Heatmaps: Mirra Chair by Herman Miller

Female Designers

Male Designers

Female Non-Designers

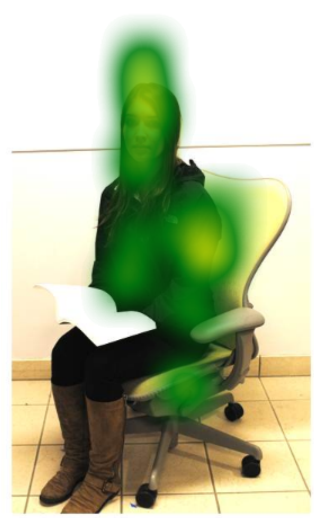
Male Non-Designers

Figure 4.16.2. Heatmaps: Mirra Chair by Herman Miller with Model

Female Designers

Male Designers

Female Non-Designers



Male Non-Designers

APPENDIX B: TABLES

Table 1.1.1. Chair Table

Chair Table				
Chair Make	**Chair Model**	**Type**	**Luminance w/o Model**	**Luminance w/ Model**
Knoll	Bertoia	Designer, Leisure	35 cd/ m^2	26 cd/ m^2
Bernhardt	Audio	Designer, Leisure	29 cd/ m^2	15.5 cd/ m^2
Knoll	Risom	Designer, Leisure	31 cd/ m^2	35 cd/ m^2
EMECO	Arm Navy	Designer, Leisure	44 cd/ m^2	35 cd/ m^2
Herman Miller	Shell	Designer, Leisure	39 cd/ m^2	24 cd/ m^2
Herman Miller	Setu	Office, Ergonomic	73 cd/ m^2	33 cd/ m^2
Steelcase	Coalesse	Office, Ergonomic	31 cd/ m^2	27 cd/ m^2
Knoll	Panton "S"	Designer, Leisure	32 cd/ m^2	20 cd/ m^2
ICF	Series 7	Designer, Leisure	54 cd/ m^2	39 cd/ m^2
Gubi!	Gubi 5	Designer, Leisure	36 cd/ m^2	27 cd/ m^2
Lifeform	Ultimate Executive	Office, Ergonomic	12.1 cd/ m^2	14.3 cd/ m^2
Herman Miller	Aeron	Designer, Leisure	10.3 cd/ m^2	10.8 cd/ m^2
Knoll	Saarinen Executive	Designer, Leisure	26 cd/ m^2	30 cd/ m^2
Humanscale	World	Office, Ergonomic	9.9 cd/ m^2	14.6 cd/ m^2
Humanscale	Freedom	Office, Ergonomic	11.4 cd/ m^2	11.8 c d/ m^2
Herman Miller	Mirra	Office Ergonomic	37 cd/ m^2	24 c d/ m^2

Table 2.1.1. Skewness and Kurtosis

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Change in Pupil Area with No Outliers	1017	-684.42	744.98	-5.8600	142.36922	.323
Change in Pupil Area	1022	-860.76	960.63	4.69	2.275	.144
Image Attractiveness	1024	1	10	4.69	2.275	.144
Model Attractiveness	512	1.00	10.00	5.3555	2.01623	-.056
Number of Fixations	1024	1	7	3.51	1.048	-.061
Average Fixation Time	1023	.20	2.00	.3982	.18228	3.587
Log Average Fixation Time	1023	-1.59	.69	-.9892	.34343	1.207
Valid N (listwise)	510					

Descriptive Statistics

	Skewness	Kurtosis	
	Std. Error	Statistic	Std. Error
Change in Pupil Area with No Outliers	.077	3.581	.153
Change in Pupil Area	.077	6.702	.153
Image Attractiveness	.076	-.913	.153
Model Attractiveness	.108	-.864	.215
Number of Fixations	.076	-.386	.153
Average Fixation Time	.076	21.272	.153
Log Average Fixation Time	.076	2.240	.153
Valid N (listwise)			

Table 3.1.1. Random Effects of Image Attractiveness Ratings

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		4.481378	.201525
ID	Variance	.625081	.204585

a. Dependent Variable: image_att.

Table 3.2.1. Comparison of Means: Image Attractiveness and Image Complexity

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	28	919.352	.000
complex	1	989.000	21.077	.000
Gender	1	28	.009	.925
DesignNoDesign	1	28	1.194	.284
complex * Gender	1	989.000	11.229	.001
complex * DesignNoDesign	1	989.000	.331	.565
Gender * DesignNoDesign	1	28	.012	.915

a. Dependent Variable: image_att.

Table 3.2.2. Comparison of Means: Image Attractiveness and Image Complexity

Estimates of Fixed Effects

Parameter	Estimate	Std. Error	df	t	Sig.
Intercept	4.975586	.329802	36.196	15.087	.000
[complex=.00]	-.240234	.229164	989.000	-1.048	.295
[Gender=1]	.447266	.456931	33.352	.979	.335
[DesignNoDesign=1]	-.380859	.456931	33.352	-.834	.410
[complex=.00] * [Gender=1]	-.886719	.264616	989.000	-3.351	.001
[complex=.00] * [DesignNoDesign=1]	.152344	.264616	989.000	.576	.565
[Gender=1] * [DesignNoDesign=1]	-.066406	.618516	28	-.107	.915

Table 3.3.1. Estimated Marginal Means: Image Attractiveness and Image Complexity

1. complex[a]

complex	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
simple	4.385	.168	39.151	4.045	4.725
complex	4.992	.168	39.151	4.652	5.332

a. Dependent Variable: image_att.

Table 3.4.1. Image Attractiveness: Image Complexity by Gender

Estimates[a]

complex	Gender	Mean	Std. Error	df	95% Confidence Interval Lower Bound	Upper Bound
simple	male	4.148	.238	39.151	3.667	4.629
	female	4.621	.238	39.151	4.140	5.102
complex	male	5.199	.238	39.151	4.718	5.680
	female	4.785	.238	39.151	4.304	5.266

a. Dependent Variable: image_att.

Table 3.4.2. Image Attractiveness: Image Complexity by Gender Pairwise Comparisons

Pairwise Comparisons[b]

complex	(I) Gender	(J) Gender	Mean Difference (I-J)	Std. Error	df	Sig.[a]
simple	male	female	-.473	.336	39.151	.168
	female	male	.473	.336	39.151	.168
complex	male	female	.414	.336	39.151	.226
	female	male	-.414	.336	39.151	.226

Table 3.4.3. Image Attractiveness: Image Complexity by Gender

Estimates[a]

complex	Gender	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
simple	male	4.148	.238	39.151	3.667	4.629
	female	4.621	.238	39.151	4.140	5.102
complex	male	5.199	.238	39.151	4.718	5.680
	female	4.785	.238	39.151	4.304	5.266

Pairwise Comparisons[a]

complex	(I) Gender	(J) Gender	Mean Difference (I-J)	Std. Error	df	Sig.[b]	95% Confidence Interval for Difference[b]	95% Confidence Interval for Difference
							Lower Bound	Upper Bound
simple	male	female	-.473	.336	39.151	.168	-1.153	.208
	female	male	.473	.336	39.151	.168	-.208	1.153
complex	male	female	.414	.336	39.151	.226	-.266	1.094
	female	male	-.414	.336	39.151	.226	-1.094	.266

a. Dependent Variable: image_att.

Table 3.4.4. Image Attractiveness: Image Complexity by Gender Univariate Test

Univariate Tests[a]

Gender	Numerator df	Denominator df	F	Sig.
male	1	989	31.537	.000
female	1	989	.769	.381

Table 3.5.1. Image Attractiveness: Image Complexity by Designer Status

Estimates[a]

complex	DesignNoDesign	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
simple	Designer	4.254	.238	39.151	3.773	4.735
	NonDesigner	4.516	.238	39.151	4.035	4.997
complex	Designer	4.785	.238	39.151	4.304	5.266
	NonDesigner	5.199	.238	39.151	4.718	5.680

a. Dependent Variable: image_att.

Table 3.5.2. Image Attractiveness: Image Complexity by Designer Status Pairwise Comparisons

Pairwise Comparisonsb

complex	(I) DesignNoDesign	(J) DesignNoDesign	Mean Difference (I-J)	Std. Error	df
simple	Designer	NonDesigner	-.262	.336	39.151
	NonDesigner	Designer	.262	.336	39.151
complex	Designer	NonDesigner	-.414	.336	39.151
	NonDesigner	Designer	.414	.336	39.151

Table 4.1.1. Random Effects of Image Attractiveness Differences

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		5.340662	.351326
Chair	Variance	.843849	.381619
ID	Variance	.813389	.293946

a. Dependent Variable: Diff_ImageAtt.

Table 4.2.1. Comparison of Means: Image Attractiveness Differences and Model Attractiveness

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	91.287	6.354	.013
ModelAttractive	1	307.057	22.312	.000

Table 4.2.2. Comparison of Means: Image Attractiveness Differences and Model Attractiveness

Estimates of Fixed Effects

Parameter	Estimate	Std. Error	df	t	Sig.
Intercept	1.238132	.491171	91.287	2.521	.013
ModelAttractive	-.344611	.072957	307.057	-4.724	.000

Table 4.3.1. Comparison of Means: Image Attractiveness Differences and Model Attractiveness

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	36.091	5.262	.028
ModelAttractive	9	464.107	4.344	.000
Gender	1	29.830	.955	.336
Design_NonDesign	1	31.279	1.010	.323
Gender * ModelAttractive	7	464.666	2.788	.008
Design_NonDesign * ModelAttractive	7	462.489	1.283	.257
Gender * Design_NonDesign	1	27.182	.334	.568

a. Dependent Variable: Diff_ImageAtt.

Table 4.3.2. Comparison of Means: Image Attractiveness Differences and Model Attractiveness

Estimates of Fixed Effectsb

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	-.874542	1.735961	476.720	-.504	.615	-4.285623	2.536538
[ModelAttractive=1]	3.042667	2.703717	480.289	1.125	.261	-2.269908	8.355242
[ModelAttractive=2]	.524215	1.843815	480.077	.284	.776	-3.098730	4.147159
[ModelAttractive=3]	.665721	1.773544	476.347	.375	.708	-2.819217	4.150659
[ModelAttractive=4]	.697409	1.799232	478.391	.388	.698	-2.837966	4.232784
[ModelAttractive=5]	.722299	1.767360	473.352	.409	.683	-2.750543	4.195140

[ModelAttractive=6]	1.153537	1.755125	473.422	.657	.511	-2.295261	4.602335
[ModelAttractive=7]	.158317	1.774062	475.437	.089	.929	-3.327655	3.644288
[ModelAttractive=8]	.593666	1.772880	469.599	.335	.738	-2.890094	4.077426
[ModelAttractive=9]	-1.945832	1.814194	467.846	-1.073	.284	-5.510810	1.619146
[Gender=1]	.736701	1.086647	246.332	.678	.498	-1.403603	2.877006
[Design_NonDesign=1]	-1.897670	1.202290	300.877	-1.578	.116	-4.263633	.468293
[Gender=1] * [ModelAttractive=2]	1.286884	1.252101	460.672	1.028	.305	-1.173655	3.747422
[Gender=1] * [ModelAttractive=3]	-.381876	1.229922	469.646	-.310	.756	-2.798707	2.034955
[Gender=1] * [ModelAttractive=4]	-.972319	1.176186	467.898	-.827	.409	-3.283580	1.338942
[Gender=1] * [ModelAttractive=5]	-1.736223	1.138904	471.700	-1.524	.128	-3.974176	.501729
[Gender=1] * [ModelAttractive=6]	-1.978042	1.128352	473.244	-1.753	.080	-4.195242	.239158
[Gender=1] * [ModelAttractive=7]	-1.178243	1.131298	473.636	-1.041	.298	-3.401226	1.044740
[Design_NonDesign=1] * [ModelAttractive=2]	2.186572	1.333807	466.882	1.639	.102	-.434436	4.807580
[Design_NonDesign=1] * [ModelAttractive=3]	1.351477	1.293861	475.307	1.045	.297	-1.190917	3.893872
[Design_NonDesign=1] * [ModelAttractive=4]	2.570978	1.257772	473.579	2.044	.041	.099474	5.042482
[Design_NonDesign=1] * [ModelAttractive=5]	2.324287	1.203574	476.277	1.931	.054	-.040685	4.689260
[Design_NonDesign=1] * [ModelAttractive=6]	1.486765	1.207115	475.964	1.232	.219	-.885169	3.858699
[Design_NonDesign=1] * [ModelAttractive=7]	2.617679	1.198463	476.705	2.184	.029	.262756	4.972602
[Design_NonDesign=1] * [ModelAttractive=8]	1.298288	1.286552	477.116	1.009	.313	-1.229721	3.826297
[Gender=1] * [Design_NonDesign=1]	-.418385	.723778	27.182	-.578	.568	-1.902989	1.066219

Table 4.4.1. Random Effects of Image Attractiveness Differences

Parameter		Estimate	Std. Error
Residual		5.123317	.345868
Chair	Variance	.861158	.389963
ID	Variance	.693153	.284721

a. Dependent Variable: Diff_ImageAtt.

Table 4.5.1. Estimated Marginal Means: Image Attractiveness Differences and Model Attractiveness

1. Model Attractive[b]

				95% Confidence Interval	
Model Attractive	Mean	Std. Error	df	Lower Bound	Upper Bound
1	.270[a]	1.753	459.411	-3.175	3.715
2	.701	.477	102.988	-.244	1.647
3	-.409	.451	99.791	-1.305	.486
4	-.063	.403	68.638	-.867	.741
5	-.543	.382	57.728	-1.307	.221
6	-.652	.384	60.217	-1.419	.116
7	-.682	.380	54.596	-1.444	.081
8	-1.397	.461	94.342	-2.313	-.481
9	-3.505	.609	214.919	-4.706	-2.305
10	-.875[a]	1.736	476.720	-4.286	2.537

a. Based on modified population marginal mean.

b. Dependent Variable: Diff_ImageAtt.

Table 4.6.1. Image Attractiveness Differences: Model Attractiveness by Gender

Estimates[c]

Model Attractive	Gender	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1	.[a]	.	.	.	.
	2	.270[b]	1.753	459.411	-3.175	3.715
2	1	1.609	.646	194.787	.334	2.883
	2	-.206	.572	135.161	-1.336	.925
3	1	-.336	.619	214.982	-1.556	.883
	2	-.482	.547	143.361	-1.563	.599
4	1	-.285	.525	130.636	-1.323	.753
	2	.160	.508	119.257	-.847	1.166
5	1	-1.148	.446	77.475	-2.035	-.260
	2	.061	.518	127.748	-.964	1.086
6	1	-1.377	.503	119.360	-2.374	-.380
	2	.074	.475	99.930	-.869	1.016
7	1	-1.007	.474	93.172	-1.948	-.066
	2	-.356	.485	97.312	-1.320	.607
8	1	-2.214	.581	166.532	-3.362	-1.066
	2	-.581	.615	165.622	-1.795	.634
9	1	-3.242	.741	265.304	-4.700	-1.784
	2	-3.769	.863	362.206	-5.466	-2.072
10	2	-.875[b]	1.736	476.720	-4.286	2.537

Table 4.6.2. Image Attractiveness Differences: Model Attractiveness by Gender Pairwise Comparisons

Pairwise Comparisons

Model Attractive	(I) Gender	(J) Gender	Mean Difference (I-J)	Std. Error	df	Sig.[c]
1	1	2	.[a,b]	.	.	.
	2	1	.[d,e]	.	.	.
2	1	2	1.814*	.761	217.873	.018
	2	1	-1.814*	.761	217.873	.018
3	1	2	.146	.741	263.213	.844
	2	1	-.146	.741	263.213	.844
4	1	2	-.445	.646	189.481	.492
	2	1	.445	.646	189.481	.492
5	1	2	-1.209*	.593	149.969	.043
	2	1	1.209*	.593	149.969	.043
6	1	2	-1.451*	.607	166.328	.018
	2	1	1.451*	.607	166.328	.018
7	1	2	-.651	.584	141.097	.267
	2	1	.651	.584	141.097	.267
8	1	2	-1.633*	.763	243.248	.033
	2	1	1.633*	.763	243.248	.033
9	1	2	.528	1.049	363.881	.615
	2	1	-.528	1.049	363.881	.615
10	1	2	.[a,b]	.	.	.
	2	1	.[d,e]	.	.	.

Table 4.7.1. Image Attractiveness Differences: Model Attractiveness by Designer Status

Estimates[c]

Model Attractive	Design_NonDesign	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	1	.270[a]	1.753	459.411	-3.175	3.715
	2	.[b]	.	.	.	.
2	1	.741	.525	115.085	-.299	1.781
	2	.661	.699	219.930	-.717	2.040
3	1	-.787	.620	212.612	-2.009	.436
	2	-.031	.544	143.597	-1.107	1.044
4	1	.169	.534	137.075	-.886	1.225
	2	-.295	.500	113.676	-1.286	.696
5	1	-.435	.457	85.235	-1.344	.475
	2	-.652	.503	115.824	-1.647	.343
6	1	-.962	.502	118.993	-1.957	.033
	2	-.342	.476	100.179	-1.286	.603
7	1	-.426	.483	95.819	-1.384	.532
	2	-.937	.475	93.987	-1.880	.006
8	1	-1.802	.602	157.506	-2.991	-.612
	2	-.993	.590	174.920	-2.157	.171
9	1	-4.559	.959	404.842	-6.445	-2.673
	2	-2.452	.678	214.288	-3.789	-1.115
10	1	.[b]	.	.	.	.
	2	-.875[a]	1.736	476.720	-4.286	2.537

a. Based on modified population marginal mean.

b. This level combination of factors is not observed, thus the corresponding population marginal mean is not estimable.

c. Dependent Variable: Diff_ImageAtt.

Table 4.7.2. Image Attractiveness Differences: Model Attractiveness by Designer Status Pairwise Comparisons

Pairwise Comparisons

Model Attractive	(I) Design_NonDesign	(J) Design_NonDesign	Mean Difference (I-J)	Std. Error
1	1	2	.[a,b]	.
	2	1	.[d,e]	.
2	1	2	.080	.788
	2	1	-.080	.788
3	1	2	-.755	.739
	2	1	.755	.739
4	1	2	.464	.649
	2	1	-.464	.649
5	1	2	.217	.584
	2	1	-.217	.584
6	1	2	-.620	.607
	2	1	.620	.607
7	1	2	.511	.582
	2	1	-.511	.582
8	1	2	-.809	.755
	2	1	.809	.755
9	1	2	-2.107	1.129
	2	1	2.107	1.129
10	1	2	.[d,e]	.
	2	1	.[a,b]	.

Table 5.1.1. Random Effects of Change in Average Pupil Area

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		20322.493080	904.339073
ID	Variance	.000000[b]	.000000

a. Dependent Variable: Change_PupilArea.

Table 5.2.1. Comparison of Means: Image Attractiveness and Change in Average Pupil Area

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	1010	.009	.924
image_att	1	1010	.582	.446
Gender	1	1010.000	1.588	.208
DesignNoDesign	1	1010.000	.059	.808
Gender * image_att	1	1010.000	1.343	.247
DesignNoDesign * image_att	1	1010.000	.488	.485
Gender * DesignNoDesign	1	1010	.015	.904

a. Dependent Variable: Change_PupilArea.

Table 5.2.2. Comparison of Means: Image Attractiveness and Change in Average Pupil Area

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
						Lower Bound
Intercept	12.037136	17.919681	1010.000	.672	.502	-23.126932
image_att	-2.427140	3.210781	1010	-.756	.450	-8.727706
[Gender=1]	-27.134509	23.071883	1010.000	-1.176	.240	-72.408823
[DesignNoDesign=1]	3.935490	22.469891	1010	.175	.861	-40.157526
[Gender=1] * image_att	4.613675	3.980934	1010.000	1.159	.247	-3.198172
[DesignNoDesign=1] * image_att	-2.774967	3.970980	1010.000	-.699	.485	-10.567283
[Gender=1] * [DesignNoDesign=1]	2.161414	17.932415	1010	.121	.904	-33.027643

Estimates of Fixed Effects[a]

Parameter	95% Confidence Interval
	Upper Bound
Intercept	47.201204
image_att	3.873425
[Gender=1]	18.139806
[DesignNoDesign=1]	48.028506
[Gender=1] * image_att	12.425523
[DesignNoDesign=1] * image_att	5.017350
[Gender=1] * [DesignNoDesign=1]	37.350472

Table 5.3.1. Estimated Marginal Means: Change in Average Pupil Area and Image Attractiveness

Estimates[a]

image_att	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
1	-12.627	18.250	993.000	-48.440	23.187
2	.988	14.660	993.000	-27.780	29.756
3	16.103	14.637	993	-12.620	44.826
4	-1.941	13.711	993	-28.847	24.964
5	-30.384	14.263	993	-58.374	-2.395
6	-7.699	14.056	993.000	-35.281	19.883
7	-6.175	15.111	993	-35.827	23.478
8	5.018	18.076	993.000	-30.453	40.489
9	36.057	27.696	993	-18.293	90.407
10	-49.598	66.241	993.000	-179.587	80.391

Table 5.4.1. Change in Average Pupil Area: Image Attractiveness by Gender

Estimates[a]

image_att	Gender	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	male	-9.274	26.549	993	-61.372	42.825
	female	-15.979	26.359	993.000	-67.706	35.747
2	male	-4.240	21.524	993.000	-46.478	37.999
	female	6.215	19.671	993.000	-32.387	44.817
3	male	20.520	20.333	993	-19.382	60.421
	female	11.687	20.415	993	-28.376	51.749
4	male	-23.640	18.631	993	-60.200	12.920
	female	19.757	20.161	993	-19.807	59.321
5	male	-30.868	19.538	993	-69.208	7.472
	female	-29.900	21.383	993	-71.861	12.060
6	male	-3.762	20.021	993.000	-43.051	35.527
	female	-11.635	19.719	993.000	-50.330	27.060
7	male	-23.217	20.856	993	-64.143	17.709
	female	10.867	21.682	993	-31.680	53.414
8	male	31.917	26.097	993.000	-19.294	83.127
	female	-21.881	25.195	993.000	-71.323	27.560
9	male	46.122	41.859	993.000	-36.021	128.265
	female	25.992	37.322	993	-47.246	99.231
10	male	35.151	116.629	993.000	-193.717	264.019
	female	-134.347	62.843	993	-257.666	-11.027

a. Dependent Variable: Change_PupilArea.

Table 5.4.2. Change in Average Pupil Area: Image Attractiveness by Gender Pairwise Comparisons

Pairwise Comparisons[a]

image_att	(I) Gender	(J) Gender	Mean Difference (I-J)	Std. Error	df	Sig.[b]	95% Confidence Interval for Difference[b]
							Lower Bound
1	male	female	6.706	38.302	993	.861	-68.456
	female	male	-6.706	38.302	993	.861	-81.868
2	male	female	-10.455	28.997	993.000	.719	-67.357
	female	male	10.455	28.997	993.000	.719	-46.448
3	male	female	8.833	28.346	993	.755	-46.793
	female	male	-8.833	28.346	993	.755	-64.459
4	male	female	-43.397	27.481	993	.115	-97.325
	female	male	43.397	27.481	993	.115	-10.531
5	male	female	-.967	29.396	993	.974	-58.653
	female	male	.967	29.396	993	.974	-56.718
6	male	female	7.873	28.091	993.000	.779	-47.252
	female	male	-7.873	28.091	993.000	.779	-62.997
7	male	female	-34.084	29.946	993.000	.255	-92.848
	female	male	34.084	29.946	993.000	.255	-24.680
8	male	female	53.798	36.396	993.000	.140	-17.625
	female	male	-53.798	36.396	993.000	.140	-125.220
9	male	female	20.130	56.762	993.000	.723	-91.257
	female	male	-20.130	56.762	993.000	.723	-131.517
10	male	female	169.498	132.482	993.000	.201	-90.480
	female	male	-169.498	132.482	993.000	.201	-429.475

Pairwise Comparisons[a]

image_att	(I) Gender	(J) Gender	95% Confidence Interval for Difference
			Upper Bound
1	male	female	81.868
	female	male	68.456
2	male	female	46.448
	female	male	67.357
3	male	female	64.459
	female	male	46.793
4	male	female	10.531
	female	male	97.325
5	male	female	56.718
	female	male	58.653
6	male	female	62.997
	female	male	47.252
7	male	female	24.680
	female	male	92.848
8	male	female	125.220
	female	male	17.625
9	male	female	131.517
	female	male	91.257
10	male	female	429.475
	female	male	90.480

Based on estimated marginal means[a]

Table 5.5.1. Change in Average Pupil Area: Image Attractiveness by Designer Status

Estimates[a]

image_att	DesignNoDesign	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
1	Designer	-4.059	27.490	993	-58.004	49.886
	NonDesigner	-21.194	25.454	993.000	-71.144	28.756
2	Designer	15.724	18.936	993.000	-21.436	52.884
	NonDesigner	-13.748	22.330	993.000	-57.568	30.072
3	Designer	1.946	17.690	993	-32.769	36.661
	NonDesigner	30.260	23.334	993	-15.530	76.050
4	Designer	-14.234	19.714	993	-52.919	24.452
	NonDesigner	10.351	19.061	993	-27.054	47.755
5	Designer	-49.642	20.960	993	-90.772	-8.511
	NonDesigner	-11.127	19.938	993.000	-50.253	28.000
6	Designer	-7.821	20.308	993	-47.672	32.030
	NonDesigner	-7.577	19.438	993.000	-45.721	30.568
7	Designer	-19.570	22.907	993.000	-64.520	25.381
	NonDesigner	7.220	19.714	993.000	-31.465	45.906
8	Designer	35.536	27.239	993.000	-17.916	88.987
	NonDesigner	-25.500	24.126	993.000	-72.844	21.844
9	Designer	-11.853	39.008	993	-88.401	64.694
	NonDesigner	83.968	40.054	993.000	5.368	162.567
10	Designer	-46.418	83.845	993.000	-210.952	118.116
	NonDesigner	-52.778	88.913	993.000	-227.257	121.702

a. Dependent Variable: Change_PupilArea.

Table 5.5.2. Change in Average Pupil Area: Image Attractiveness by Designer Status Pairwise Comparisons

Pairwise Comparisons[a]

image_att	(I) DesignNoDesign	(J) DesignNoDesign	Mean Difference (I-J)	Std. Error	df
1	Designer	NonDesigner	17.135	38.405	993
	NonDesigner	Designer	-17.135	38.405	993
2	Designer	NonDesigner	29.472	29.237	993.000
	NonDesigner	Designer	-29.472	29.237	993.000
3	Designer	NonDesigner	-28.315	29.290	993
	NonDesigner	Designer	28.315	29.290	993
4	Designer	NonDesigner	-24.584	27.422	993
	NonDesigner	Designer	24.584	27.422	993
5	Designer	NonDesigner	-38.515	29.325	993.000
	NonDesigner	Designer	38.515	29.325	993.000
6	Designer	NonDesigner	-.244	28.111	993
	NonDesigner	Designer	.244	28.111	993
7	Designer	NonDesigner	-26.790	30.222	993.000
	NonDesigner	Designer	26.790	30.222	993.000
8	Designer	NonDesigner	61.036	36.621	993.000
	NonDesigner	Designer	-61.036	36.621	993.000
9	Designer	NonDesigner	-95.821	56.423	993.000
	NonDesigner	Designer	95.821	56.423	993.000
10	Designer	NonDesigner	6.360	110.994	993.000
	NonDesigner	Designer	-6.360	110.994	993.000

Pairwise Comparisons[a]

image_att	(I) DesignNoDesign	(J) DesignNoDesign	Sig.	95% Confidence Interval for Difference	
				Lower Bound	Upper Bound
1	Designer	NonDesigner	.656	-58.229	92.500
	NonDesigner	Designer	.656	-92.500	58.229
2	Designer	NonDesigner	.314	-27.901	86.845
	NonDesigner	Designer	.314	-86.845	27.901
3	Designer	NonDesigner	.334	-85.792	29.163
	NonDesigner	Designer	.334	-29.163	85.792
4	Designer	NonDesigner	.370	-78.396	29.227
	NonDesigner	Designer	.370	-29.227	78.396
5	Designer	NonDesigner	.189	-96.061	19.030
	NonDesigner	Designer	.189	-19.030	96.061
6	Designer	NonDesigner	.993	-55.408	54.920
	NonDesigner	Designer	.993	-54.920	55.408
7	Designer	NonDesigner	.376	-86.096	32.516
	NonDesigner	Designer	.376	-32.516	86.096
8	Designer	NonDesigner	.096	-10.827	132.899
	NonDesigner	Designer	.096	-132.899	10.827
9	Designer	NonDesigner	.090	-206.542	14.901
	NonDesigner	Designer	.090	-14.901	206.542
10	Designer	NonDesigner	.954	-211.449	224.169
	NonDesigner	Designer	.954	-224.169	211.449

Table 6.1.1. Random Effects of Average Pupil Area

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		19500.846875	866.918386
ID	Variance	.000000[b]	.000000

a. Dependent Variable: Change_PupilArea.

Table 6.2.1. Comparison of Means: Change in Average Pupil Area and Image Luminance

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	1012.000	20.245	.000
image_att	1	1012.000	.772	.380
Luminance	1	1012.000	42.287	.000
Gender	1	1012.000	.217	.641
DesignNoDesign	1	1012	.852	.356

a. Dependent Variable: Change_PupilArea.

Table 6.2.2. Comparison of Means: Change in Average Pupil Area and Luminance

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
						Lower Bound
Intercept	66.978596	15.077218	1012	4.442	.000	37.392407
image_att	-1.696722	1.930635	1012.000	-.879	.380	-5.485229
Luminance	-2.095479	.322240	1012.000	-6.503	.000	-2.727813
[Gender=1]	-4.080817	8.758187	1012.000	-.466	.641	-21.267103
[DesignNoDesign=1]	-8.104341	8.781933	1012	-.923	.356	-25.337224

Estimates of Fixed Effects[a]

Parameter	95% Confidence Interval
	Upper Bound
Intercept	96.564785
image_att	2.091784
Luminance	-1.463144
[Gender=1]	13.105469
[DesignNoDesign=1]	9.128542

Table 7.1.1. Random Effects of Change in Average Pupil Area

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		19790.813959	1247.942748
ID	Variance	.000000[b]	.000000

a. Dependent Variable: Change_PupilArea.

Table 7.2.1. Comparison of Means: Change in Average Pupil Area and Face Luminance

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	503	3.275	.071
image_att	1	503	.695	.405
Facial_Lum	1	503	1.612	.205
Gender	1	503	.913	.340
DesignNoDesign	1	503	1.983	.160

a. Dependent Variable: Change_PupilArea.

Table 7.2.2. Comparison of Means: Average Pupil Area and Face Luminance

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
						Lower Bound
Intercept	116.442960	56.775678	503	2.051	.041	4.896275
image_att	-2.556977	3.067118	503	-.834	.405	-8.582917
Facial_Lum	-1.332375	1.049429	503	-1.270	.205	-3.394179
[Gender=1]	-11.990246	12.547196	503	-.956	.340	-36.641614
[DesignNoDesign=1]	-17.671056	12.550153	503	-1.408	.160	-42.328233

Estimates of Fixed Effects[a]

Parameter	95% Confidence Interval
	Upper Bound
Intercept	227.989646
image_att	3.468963
Facial_Lum	.729430
[Gender=1]	12.661123
[DesignNoDesign=1]	6.986121

a. Dependent Variable: Change_PupilArea.

Table 8.1.1. Random Effects of Subject ID

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		2.616479	.169423
ID	Variance	1.239167	.368519

a. Dependent Variable: model_att.

Table 8.2.1. Comparison of Means: Facial Luminance and Model Attractiveness

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	488.867	.659	.417
Facial_Lum	1	477.000	59.432	.000
Gender	1	488.867	.121	.728
DesignNoDesign	1	488.867	.198	.657
Gender * Facial_Lum	1	477	.273	.601
DesignNoDesign * Facial_Lum	1	477.000	.562	.454

a. Dependent Variable: model_att.

Table 8.2.2. Comparison of Means: Facial Luminance and Model Attractiveness

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
						Lower Bound
Intercept	.471485	1.142037	488.867	.413	.680	-1.772421
Facial_Lum	.095311	.020801	477.000	4.582	.000	.054438
[Gender=1]	-.458267	1.318710	488.867	-.348	.728	-3.049306
[DesignNoDesign=1]	.586119	1.318710	488.867	.444	.657	-2.004920
[Gender=1] * Facial_Lum	.012554	.024019	477	.523	.601	-.034641
[DesignNoDesign=1] * Facial_Lum	-.018011	.024019	477.000	-.750	.454	-.065206

Estimates of Fixed Effects[a]

Parameter	95% Confidence Interval
	Upper Bound
Intercept	2.715391
Facial_Lum	.136183
[Gender=1]	2.132773
[DesignNoDesign=1]	3.177159
[Gender=1] * Facial_Lum	.059749
[DesignNoDesign=1] * Facial_Lum	.029184

Table 9.1.1. Random Effects of Number of Fixations

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		20369.633349	906.436787
ID	Variance	.000000[b]	.000000

a. Dependent Variable: Change_PupilArea.

Table 9.2.1. Comparison of Means: Change in Average Pupil Area and Number of Fixations

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	1010	.143	.705
NumberFixations	1	1010	.000	.994
Gender	1	1010	.035	.852
DesignNoDesign	1	1010	.152	.697
Gender * NumberFixations	1	1010.000	.003	.958
DesignNoDesign * NumberFixations	1	1010.000	.025	.875
Gender * DesignNoDesign	1	1010	.001	.971

Table 9.2.2. Comparison of Means: Change in Average Pupil Area and Number of Fixations

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
						Lower Bound
Intercept	3.282560	27.518630	1010	.119	.905	-50.717675
NumberFixations	-.872625	7.593630	1010.000	-.115	.909	-15.773724
[Gender=1]	-6.209530	33.159692	1010	-.187	.851	-71.279310
[DesignNoDesign=1]	-12.619337	32.090293	1010	-.393	.694	-75.590617
[Gender=1] * NumberFixations	.452672	8.625473	1010.000	.052	.958	-16.473228
[DesignNoDesign=1] * NumberFixations	1.352549	8.605867	1010.000	.157	.875	-15.534878
[Gender=1] * [DesignNoDesign=1]	.644119	17.991437	1010	.036	.971	-34.660758

Estimates of Fixed Effects[a]

Parameter	95% Confidence Interval
	Upper Bound
Intercept	57.282796
NumberFixations	14.028473
[Gender=1]	58.860249
[DesignNoDesign=1]	50.351944
[Gender=1] * NumberFixations	17.378572
[DesignNoDesign=1] * NumberFixations	18.239976
[Gender=1] * [DesignNoDesign=1]	35.948996

a. Dependent Variable: Change_PupilArea.

Table 10.1.1. Random Effects of Change in Average Pupil Area

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		20377.889840	907.253443
ID	Variance	.000000[b]	.000000

a. Dependent Variable: Change_PupilArea.

Table 10.2.1. Comparison of Means: Change in Average Pupil Area and Log Average Fixation Time

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	1009	.472	.492
ln_AveFixTime	1	1009	.087	.768
Gender	1	1009	.360	.549
DesignNoDesign	1	1009	.119	.730
Gender * ln_AveFixTime	1	1009	.208	.649
DesignNoDesign * ln_AveFixTime	1	1009.000	.412	.521
Gender * DesignNoDesign	1	1009	.001	.979

a. Dependent Variable: Change_PupilArea.

Table 10.2.2. Comparison of Means: Change in Average Pupil Area and Log Average Fixation Time

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-5.790833	23.120517	1009.000	-.250	.802	-51.160638	39.578971
ln_AveFixTime	-6.393043	22.410978	1009	-.285	.776	-50.370507	37.584420
[Gender=1]	-17.152660	29.086426	1009	-.590	.556	-74.229473	39.924153
[DesignNoDesign=1]	9.492413	29.924717	1009.000	.317	.751	-49.229393	68.214220
[Gender=1] * ln_AveFixTime	-12.222694	26.818138	1009	-.456	.649	-64.848406	40.403018
[DesignNoDesign=1] * ln_AveFixTime	17.219473	26.827210	1009.000	.642	.521	-35.424041	69.862987
[Gender=1] * [DesignNoDesign=1]	.472758	18.041221	1009	.026	.979	-34.929853	35.875368

a. Dependent Variable: Change_PupilArea.

Table 11.1.1. Random Effects of Change in Average Pupil Area

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		19930.921215	1259.283484
ID	Variance	.000000[b]	.000000

a. Dependent Variable: Change_PupilArea.

Table 11.2.1. Comparison of Means: Change in Average Pupil Area and Model Attractiveness

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	501	1.358	.244
model_att	1	501.000	.016	.901
Gender	1	501	.892	.345
DesignNoDesign	1	501.000	.015	.902
Gender * model_att	1	501	.398	.528
DesignNoDesign * model_att	1	501	.406	.524
Gender * DesignNoDesign	1	501	.222	.638

a. Dependent Variable: Change_PupilArea.

Table 11.2.2. Comparison of Means: Change in Average Pupil Area and Model Attractiveness

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	38.754933	30.907767	501	1.254	.210	-21.969876	99.479742
model_att	-.375420	5.126679	501	-.073	.942	-10.447860	9.697020
[Gender=1]	-40.002663	39.210337	501	-1.020	.308	-117.039617	37.034292
[DesignNoDesign=1]	-1.516220	37.399364	501	-.041	.968	-74.995137	71.962697
[Gender=1] * model_att	3.976992	6.304937	501	.631	.528	-8.410383	16.364367
[DesignNoDesign=1] * model_att	-4.007122	6.285552	501	-.638	.524	-16.356410	8.342167
[Gender=1] * [DesignNoDesign=1]	11.876653	25.218697	501	.471	.638	-37.670782	61.424089

Table 12.1.1. Random Effect of Change in Average Pupil Area

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		19682.307537	875.851190
ID	Variance	.000000[b]	.000000

a. Dependent Variable: Change_PupilArea.

Table 12.2.1. Comparison of Means: Image Complexity and Change in Average Pupil Area

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	1010.000	1.785	.182
complex	1	1010	33.111	.000
Gender	1	1010	.220	.639
DesignNoDesign	1	1010	.734	.392
Gender * complex	1	1010	1.050	.306
DesignNoDesign * complex	1	1010	1.074	.300
Gender * DesignNoDesign	1	1010	.002	.963

a. Dependent Variable: Change_PupilArea.

Table 12.2.2. Comparison of Means: Image Complexity and Change in Average Pupil Area

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
						Lower Bound
Intercept	34.538693	11.605147	1010	2.976	.003	11.765732
[complex=.00]	-68.763687	15.224654	1010	-4.517	.000	-98.639262
[Gender=1]	-13.545905	15.224654	1010	-.890	.374	-43.421480
[DesignNoDesign=1]	-17.067120	15.204661	1010.000	-1.122	.262	-46.903463
[Gender=1] * [complex=.00]	18.030296	17.597349	1010	1.025	.306	-16.501255
[DesignNoDesign=1] * [complex=.00]	18.238682	17.597349	1010	1.036	.300	-16.292869
[Gender=1] * [DesignNoDesign=1]	.816234	17.597418	1010	.046	.963	-33.715453

Estimates of Fixed Effects[a]

Parameter	95% Confidence Interval
	Upper Bound
Intercept	57.311653
[complex=.00]	-38.888113
[Gender=1]	16.329669
[DesignNoDesign=1]	12.769222
[Gender=1] * [complex=.00]	52.561847
[DesignNoDesign=1] * [complex=.00]	52.770234
[Gender=1] * [DesignNoDesign=1]	35.347920

Table 12.3.1. Estimated Marginal Means: Change in Average Pupil Area and Image Complexity

complex[a]

complex	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
simple	-31.193	6.218	1010	-43.395	-18.990
complex	19.436	6.225	1010.000	7.221	31.651

a. Dependent Variable: Change_PupilArea.

Table 13.1.1. Random Effects of Number of Fixations

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		.956423	.043010
ID	Variance	.107798	.036823

a. Dependent Variable: NumberFixations.

Table 13.2.1. Comparison of Means: Average Number of Fixations and Image Complexity

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	28.000	2856.586	.000
complex	1	989	34.569	.000
Gender	1	28.000	1.348	.255
DesignNoDesign	1	28.000	.599	.445
complex * Gender	1	989	5.293	.022
complex * DesignNoDesign	1	989	5.591	.018
Gender * DesignNoDesign	1	28.000	.599	.445

a. Dependent Variable: NumberFixations.

Table 13.2.2. Comparison of Means: Average Number of Fixations and Image Complexity

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	3.392578	.141467	37.831	23.981	.000	3.106152	3.679005
[complex=.00]	.074219	.105868	989	.701	.483	-.133533	.281971
[Gender=1]	.113281	.195340	34.396	.580	.566	-.283529	.510091
[DesignNoDesign=1]	-.144531	.195340	34.396	-.740	.464	-.541341	.252279
[complex=.00] * [Gender=1]	.281250	.122246	989	2.301	.022	.041358	.521142
[complex=.00] * [DesignNoDesign=1]	.289063	.122246	989	2.365	.018	.049171	.528954
[Gender=1] * [DesignNoDesign=1]	-.203125	.262380	28.000	-.774	.445	-.740586	.334336

Table 13.3.1. Average Number of Fixations and Complexity

Estimates[a]

complex	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
simple	3.686	.072	41.420	3.539	3.832
complex	3.326	.072	41.420	3.180	3.472

Table 13.3.2. Average Number of Fixations and Complexity Pairwise Comparisons

Pairwise Comparisonsb

(I) complex	(J) complex	Mean Difference (I-J)	Std. Error	df	Sig.[a]
simple	complex	.359*	.061	989.000	.000
complex	simple	-.359*	.061	989.000	.000

Table 13.4.1. Average Number of Fixations: Image Complexity by Gender

Estimates[a]

complex	Gender	Mean	Std. Error	df	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
simple	male	3.832	.102	41.420	3.625	4.039
	female	3.539	.102	41.420	3.332	3.746
complex	male	3.332	.102	41.420	3.125	3.539
	female	3.320	.102	41.420	3.114	3.527

Pairwise Comparisons

complex	(I) Gender	(J) Gender	Mean Difference (I-J)	Std. Error	df	Sig.[a]
simple	male	female	.293*	.145	41.420	.049
	female	male	-.293*	.145	41.420	.049
complex	male	female	.012	.145	41.420	.936
	female	male	-.012	.145	41.420	.936

Table 13.4.2. Average Number of Fixations: Image Complexity by Gender Univariate Test

Univariate Tests[a]

complex	Numerator df	Denominator df	F	Sig.
simple	1	41.420	4.098	.049
complex	1	41.420	.007	.936

Table 13.4.3. Average Number of Fixations: Gender by Image Complexity

Estimates[a]

complex	Gender	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
simple	male	3.832	.102	41.420	3.625	4.039
	female	3.539	.102	41.420	3.332	3.746
complex	male	3.332	.102	41.420	3.125	3.539
	female	3.320	.102	41.420	3.114	3.527

Pairwise Comparisons[a]

Gender	(I) complex	(J) complex	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
male	simple	complex	.500*	.086	989	.000	.330	.670*
	complex	simple	-.500*	.086	989	.000	-.670	-.330*
female	simple	complex	.219*	.086	989	.012	.049	.388*
	complex	simple	-.219*	.086	989	.012	-.388	-.049*

Table 13.4.4. Average Number of Fixations: Gender by Image Complexity Univariate Test

Univariate Tests[a]

Gender	Numerator df	Denominator df	F	Sig.
male	1	989	33.458	.000
female	1	989	6.404	.012

Table 13.5.1. Average Number of Fixations: Image Complexity by Designer Status

Estimates[a]

					95% Confidence Interval	
DesignNoDesign	complex	Mean	Std. Error	df	Lower Bound	Upper Bound
Designer	simple	3.707	.102	41.420	3.500	3.914
	complex	3.203	.102	41.420	2.997	3.410
NonDesigner	simple	3.664	.102	41.420	3.457	3.871
	complex	3.449	.102	41.420	3.243	3.656

a. Dependent Variable: NumberFixations.

Table 13.5.2. Average Number of Fixations: Image Complexity by Designer Status Pairwise Comparisons

Pairwise Comparisons

DesignNoDesign	(I) complex	(J) complex	Mean Difference (I-J)	Std. Error	df	Sig.[a]
Designer	simple	complex	.504*	.086	989.000	.000
	complex	simple	-.504*	.086	989.000	.000
NonDesigner	simple	complex	.215*	.086	989.000	.013
	complex	simple	-.215*	.086	989.000	.013

Table 13.5.3. Average Number of Fixations: Image Complexity by Designer Status Univariate Test

Univariate Tests[a]

DesignNoDesign	Numerator df	Denominator df	F	Sig.
Designer	1	989	33.983	.000
NonDesigner	1	989	6.177	.013

Table 13.5.4. Average Number of Fixations: Designer Status by Image Complexity

Pairwise Comparisons[a]

complex	(I) DesignNoDesign	(J) DesignNoDesign	Sig.	95% Confidence Interval for Difference	
				Lower Bound	Upper Bound
simple	Designer	NonDesigner	.768	-.249	.335
	NonDesigner	Designer	.768	-.335	.249
complex	Designer	NonDesigner	.097	-.538	.046
	NonDesigner	Designer	.097	-.046	.538

Table 13.5.5. Average Number of Fixations: Designer Status by Image Complexity Univariate Test

Univariate Tests[a]

complex	Numerator df	Denominator df	F	Sig.
simple	1	41.420	.088	.768
complex	1	41.420	2.891	.097

Table 14.1.1. Random Effects of Log Average Fixation Time

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		.082116	.003713
ID	Variance	.015663	.004882

a. Dependent Variable: ln_AveFixationTime.

Table 14.2.1. Comparison of Means: Log Average Fixation Time and Image Complexity

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	27.986	1758.133	.000
complex	1	978.112	25.252	.000
Gender	1	27.986	.393	.536
DesignNoDesign	1	27.986	.638	.431
complex * Gender	1	978.112	.799	.372
complex * DesignNoDesign	1	978.112	5.036	.025
Gender * DesignNoDesign	1	27.986	1.816	.189

a. Dependent Variable: ln_AveFixationTime.

Table 14.2.2. Comparison of Means: Log Average Fixation Time and Image Complexity

Estimates of Fixed Effects

Parameter	Estimate	Std. Error	df	t	Sig.
Intercept	-.948286	.050201	34.113	-18.890	.000
[complex=.00]	-.033984	.031165	978.117	-1.090	.276
[Gender=1]	-.018303	.069887	32.040	-.262	.795
[DesignNoDesign=1]	-.062111	.069926	32.110	-.888	.381
[complex=.00] * [Gender=1]	-.032207	.036023	978.112	-.894	.372
[complex=.00] * [DesignNoDesign=1]	-.080842	.036023	978.112	-2.244	.025
[Gender=1] * [DesignNoDesign=1]	.128740	.095546	27.986	1.347	.189

Table 14.3.1. Estimated Marginal Means: Log Average Fixation Time and Image Complexity

1. complex[a]

complex	Mean	Std. Error	df	95% Confidence Interval	
				Lower Bound	Upper Bound
simple	-1.047	.026	36.394	-1.099	-.995
complex	-.956	.026	36.579	-1.008	-.905

a. Dependent Variable: ln_AveFixationTime.

Table 14.4.1. Log Average Fixation Time: Image Complexity by Gender

Estimates[a]

complex	Gender	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
simple	male	-1.040	.036	36.357	-1.113	-.967
	female	-1.054	.036	36.432	-1.127	-.981
complex	male	-.933	.036	36.651	-1.007	-.860
	female	-.979	.036	36.505	-1.053	-.906

a. Dependent Variable: ln_AveFixationTime.

Table 14.4.2. Log Average Fixation Time: Image Complexity by Gender Pairwise Comparisons

Pairwise Comparisons

complex	(I) Gender	(J) Gender	Mean Difference (I-J)	Std. Error	df	Sig.[a]
simple	male	female	.014	.051	36.394	.787
	female	male	-.014	.051	36.394	.787
complex	male	female	.046	.051	36.577	.373
	female	male	-.046	.051	36.577	.373

Table 14.5.1. Log Average Fixation Time: Designer Status by Image Complexity

Pairwise Comparisons[a]

DesignNoDesign	(I) complex	(J) complex	Mean Difference (I-J)	Std. Error	df	Sig.[c]
Designer	simple	complex	-.164*	.027	988.003	.000
	complex	simple	.164*	.027	988.003	.000
NonDesigner	simple	complex	-.034	.027	988.018	.219
	complex	simple	.034	.027	988.018	.219

Pairwise Comparisons[a]

DesignNoDesign	(I) complex	(J) complex	95% Confidence Interval for Difference	
			Lower Bound	Upper Bound
Designer	simple	complex	-.218*	-.110
	complex	simple	.110*	.218
NonDesigner	simple	complex	-.088	.020
	complex	simple	-.020	.088

Table 14.5.2. Log Average Fixation Time: Designer Status by Image Complexity Univariate Test

Univariate Tests[a]

DesignNoDesign	Numerator df	Denominator df	F	Sig.
Designer	1	988.003	35.668	.000
NonDesigner	1	988.018	1.514	.219

Table 14.5.3. Log Average Fixation Time: Image Complexity by Designer Status

Pairwise Comparisons[a]

complex	(I) DesignNoDesign	(J) DesignNoDesign	Mean Difference (I-J)	Std. Error	df
simple	Designer	NonDesigner	-.095	.056	36.050
	NonDesigner	Designer	.095	.056	36.050
complex	Designer	NonDesigner	.035	.056	36.084
	NonDesigner	Designer	-.035	.056	36.084

Pairwise Comparisons[a]

complex	(I) DesignNoDesign	(J) DesignNoDesign	Sig.	95% Confidence Interval for Difference	
				Lower Bound	Upper Bound
simple	Designer	NonDesigner	.100	-.209	.019
	NonDesigner	Designer	.100	-.019	.209
complex	Designer	NonDesigner	.536	-.079	.149
	NonDesigner	Designer	.536	-.149	.079

Table 14.5.4. Log Average Fixation Time: Image Complexity by Designer Status Univariate Test

Univariate Tests[a]

complex	Numerator df	Denominator df	F	Sig.
simple	1	36.050	2.846	.100
complex	1	36.084	.391	.536

Table 15.1.1. Random Effects of Image Attractiveness

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error
Residual		.099252	.004466
ID	Variance	.017199	.005459

a. Dependent Variable: ln_AveFixTime.

Table 15.2.1. Comparison of Means: Log Average Fixation Time and Image Attractiveness

Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	79.864	1000.684	.000
image_att	1	1015.009	8.218	.004
Gender	1	81.574	.218	.642
DesignNoDesign	1	81.354	1.004	.319
Gender * image_att	1	1015.957	1.874	.171
DesignNoDesign * image_att	1	1015.985	.904	.342
Gender * DesignNoDesign	1	27.735	2.104	.158

a. Dependent Variable: ln_AveFixTime.

Table 15.2.2. Comparison of Means: Average Fixation Time and Image Attractiveness

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
						Lower Bound
Intercept	-.964805	.061713	61.045	-15.634	.000	-1.088205
image_att	.002354	.007342	1009.598	.321	.749	-.012053
[Gender=1]	-.104370	.084577	53.588	-1.234	.223	-.273967
[DesignNoDesign=1]	-.140113	.083661	51.437	-1.675	.100	-.308036
[Gender=1] * image_att	.012861	.009396	1015.957	1.369	.171	-.005576
[DesignNoDesign=1] * image_att	.008919	.009378	1015.985	.951	.342	-.009484
[Gender=1] * [DesignNoDesign=1]	.146205	.100804	27.735	1.450	.158	-.060372

Estimates of Fixed Effects[a]

Parameter	95% Confidence Interval
	Upper Bound
Intercept	-.841405
image_att	.016761
[Gender=1]	.065226
[DesignNoDesign=1]	.027810
[Gender=1] * image_att	.031298
[DesignNoDesign=1] * image_att	.027321
[Gender=1] * [DesignNoDesign=1]	.352782